GPS 3.0: from distance into zones toward better proxies of internal neuromuscular load in elite football

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In collaboration with

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GPS 3.0 | Neuromuscular load | External load proxy | Direction-sensitive mechanics | Mechanical work & mechanical power | Movement signatures | Peak demands (MIPs) | Intensity exposure time (IET/WIET) | Capacity-based anchoring (Estimated Maximal MP$_{\mathbf{1min}}$) | Dose–response & injury risk

Headline

Over the past two decades, Global Positioning System (GPS) technology has become the dominant monitoring tool in elite football (Dawson 2024; Gualtieri 2023). GPS 1.0 was developed to describe match locomotor demands rather than to quantify training load (Aughey 2011; Buchheit, Mendez-villanueva et al. 2010; Wisbey 2010). Early low-frequency systems (≈1 Hz) were therefore used to inform conditioning by profiling match running and positional demands.

Hardware and processing improvements (Cummins 2013; Bataller-Cervero 2019; Gimenez 2020; Hoppe 2018) expanded available variables and enabled GPS 2.0, including metabolic power estimates (Osgnach 2010) and normative benchmarks (Ravé 2020). GPS also shifted from describing competition demands to informing training monitoring and prescription. GPS-derived metrics are now used to guide training prescription (Little & Buchheit 2025), evaluate return-to-play readiness (Buchheit, Balaña et al. 2025; Buchheit, King et al. 2023; Taberner 2025a; 2025b), and inform injury risk management (Buchheit, Settembre et al. 2024; Jiang 2022).

Importantly, this evolution should not be interpreted as a failure of GPS 2.0 metrics, nor as a dismissal of the substantial body of research built upon them. Distance-, speed-, and linear acceleration-based variables remain useful for characterising match demands, comparing training contents (Malone 2015), and exploring associations with outcomes such as injury occurrence (Buchheit, Settembre et al. 2024; Jiang 2022), muscle damage, and neuromuscular fatigue (Hader 2019). Much of our own work has relied on these metrics to advance understanding and inform practice. The limitation is conceptual: within a load–response framework (Buchheit & Hader 2025), GPS quantifies external locomotor load and can only serve as an indirect proxy for internal neuromuscular load. In an ideal world, neuromuscular load would be captured via internal measures more directly linked to tissue stress and fatigue, such as muscle activation (e.g., EMG; Kalema 2025), muscle–tendon stress/strain, or even bone loading (Kalkhoven 2021), but these approaches are impractical and unscalable in elite football. In practice, GPS has become the least-bad scalable option; the issue is the GPS 2.0 interpretive drift whereby descriptive movement outputs are treated as biological truths, inflating what GPS can legitimately tell us about neuromuscular loading (Buchheit & Hader 2025).

This paper argues that elite football has reached the limits of GPS 2.0, an era dominated by distance accumulation, speed zones, and ratio-based logic (Buchheit & Laursen 2024; Little & Buchheit, 2025). What is now required is a transition to GPS 3.0: not another technological upgrade, but a conceptual reset, one that preserves GPS as an important tool for understanding football (neuromuscular) demands, while fundamentally improving how its data are interpreted in relation to locomotor actions mechanics, intensity structure, and in turn, internal neuromuscular load.

Aim

This commentary has three aims. First, to position GPS within contemporary monitoring frameworks as a measure of external locomotor load and a proxy, not a direct measure, of internal neuromuscular load (Buchheit & Hader 2025). Second, to explain why common GPS 2.0 practices, dominated by distance in speed zones, averages, and ratio-based targets, are poorly suited to quantify neuromuscular load when used beyond their original descriptive purpose, while acknowledging their applied value in elite football (Buchheit & Laursen 2024; Little & Buchheit 2025). Third, to outline a GPS 3.0 transition that prioritises direction-sensitive, mechanically grounded analyses to better describe intensity structure and exposure, and to distinguish immediately actionable steps from exposure constructs that remain method-dependent and require further validation.

Tiered transition to GPS 3.0: practical implications and implementation readiness

This commentary supports a tiered transition to GPS 3.0 because implementation readiness differs across its components. Direction-sensitive analytics that quantify complete acceleration, true mechanical work and movement signatures (e.g., ADI-derived outputs; Figures 7–9) are a low-regret step that can be adopted immediately, as they correct a structural limitation of GPS 2.0, underestimating multidirectional mechanics by treating speed as the main indicator of intensity.

In contrast, mechanical power exposure constructs (time above thresholds, IET) are conceptually strong but not yet "ready-made" metrics. They remain method-dependent, particularly for threshold selection and the choice of analysis windows. Current rolling windows can yield low accumulated time at high relative intensities (Tables 3–5), which challenges sensitivity; yet some windowing is still required. Removing windows and reverting to accumulated time/totals at high mechanical power would recreate GPS 2.0 logic, where quantity dominates and the structure of effort is lost. Window-based analysis is needed to retain information on sustained high-intensity passages most likely to drive fatigue, consistent with Bundle's speed–duration framework (2003) (Figures 15–16).

GPS 3.0 should therefore start with mechanically correct descriptors now, and progress toward exposure models as calibration improves and evidence accumulates.

Repositioning GPS within the monitoring framework

Any meaningful discussion about GPS must begin with conceptual clarity. Within a quadrant-based monitoring framework that distinguishes load from response and metabolic from neuromuscular domains, GPS occupies a very specific position in the upper-right quadrant. (Figure 1, Buchheit & Hader, 2025). GPS quantifies external load, and more precisely, external locomotor activity that may contribute to neuromuscular loading (i.e., mechanical load at the tissue level, Kalkhoven et al., 2021).

However, what GPS does not measure is internal neuromuscular strain or load itself, i.e., the true "internal, neuromuscular load". It does not capture muscle–tendon stress and strain, mechanically induced tissue damage or neural fatigue. At best, GPS-derived variables provide indirect and weak proxies that may or may not reflect the internal stresses experienced by the player. Importantly, adaptation and injury risk are driven by internal load, not by movement outputs per se (Impellizzeri et al., 2019; Buchheit & Laursen, 2019).

This distinction is not semantic; it is foundational. When external metrics are treated as biological truths, the dose–response relationship that underpins training theory is distorted. GPS does not become problematic because it lacks accuracy, but because it is often used outside its conceptual lane. The widespread use of "GPS targets," high-speed running quotas, or fixed sprint distance benchmarks illustrates this confusion (Little & Buchheit 2025). This drift is amplified when external locomotor numbers are treated as objectives of session design rather than as outputs of football problem-solving. Overall, these practices implicitly assume a stable and direct relationship between meters run and internal neuromuscular load, an assumption that does not hold in a sport as complex and context-dependent as football.

Why traditional GPS metrics fail to accurately quantify neuromuscular load

Same external load does not mean same internal neuromuscular load

One of the most fundamental limitations of GPS-derived metrics is that identical external loads can result in very different internal neuromuscular loads. Two players may accumulate the same high-speed running distance yet experience markedly different internal stress depending on their physical capacities, injury history, fatigue state, movement variability, decision-making demands, opposition pressure, or technical involvement.

More fundamentally, GPS is extrinsic to the biological system: it tracks the displacement of a wearable device (a moving object in space), not the forces the athlete must generate to produce that motion. As a result, it cannot account for key environmental modifiers (e.g., firmer vs softer surfaces, inclines vs declines, headwinds vs tailwinds) that alter force requirements for the same observed speed/acceleration. Likewise, it cannot capture high-force interactions with another object or an opponent that involve substantial internal loading with minimal displacement (e.g., shielding/holding off an opponent to keep possession, wrestling for position; analogous examples include scrums or static grappling in other team sports).

Critically, inter-individual differences in muscle fiber type further amplify this dissociation. The pioneering work of Wim Derave and colleagues has highlighted the central role of muscle fiber typology in performance, fatigue, and recovery (Bellinger et al., 2020; Lievens et al., 2020, 2022; Van Vossel et al., 2023). For a given external workload, fast-twitch–dominant athletes typically experience greater acute neuromuscular fatigue and require longer recovery than slow-twitch–dominant athletes. As a result, "same load" does not equate to "same strain," even when GPS metrics appear identical.

This inter-individual variability reinforces why external metrics can only serve as indirect proxies of internal neuromuscular load, and why interpreting GPS data without accounting for biological context risks masking meaningful differences in fatigue and recovery.

Football movement is not pre-planned running. It emerges from continuously evolving perceptual and tactical constraints. Sprinting into open space following anticipation of play is neuromuscularly different from sprinting reactively under defensive pressure, even if peak speed and distance are identical. This distinction is supported by the literature comparing official matches with match simulations (where similar volumes and intensities are reproduced in an isolated, non-specific manner), which consistently shows that actual games induce greater muscle damage, inflammatory and immunological responses, and delayed onset muscle soreness than simulations (Silva 2018). GPS captures what happened, but not how or why it happened. This is precisely why 'planning from running load' is conceptually upside down: football constraints create running behaviours, not the reverse (Mandorino 2025, Buchheit & Verheijen, Training Podcast, Episode #99).

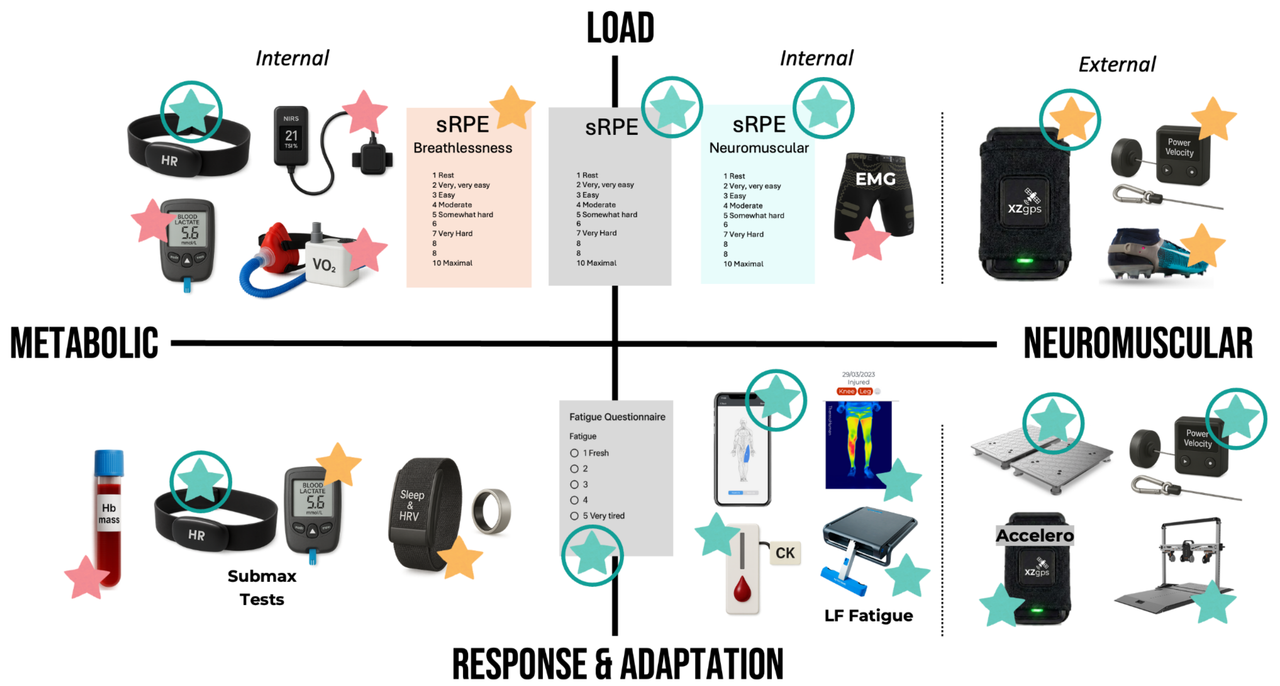


Fig. 1. Tools available mapped according to the quadrant-based monitoring framework that distinguishes load from response and metabolic from neuromuscular domains. GPS stands in the upper right quadrant as (only) a proxy of neuromuscular load. The color of the stars reflects a combination of validity, practicality, and cost, ranging from green (ideal) to red (impractical and/or limited) (for more explanations, see Tables 2–5 in Buchheit & Hader 2025). Stars with a circle indicate the recommended practical minimum setup. Non-biological system-specific subjective ratings such as sRPE (load) and sleep, fatigue, mood, or recovery (response) are positioned between quadrants, as they likely reflect, influence or are associated with both metabolic and neuromuscular domains. While sleep is neither a direct metabolic nor neuromuscular response, it serves as both an indicator of overall wellness and a modulator of training response. Poor sleep is typically associated with increased fatigue and reduced training quality, which can ultimately affect the magnitude and direction of adaptation. ADI: athletic data innovation (https://www.adi-data.co/), CK: creatine phosphokinase, EMG: electromyography, GPS: global positioning system, Hbmass: hemoglobin mass, HR: heart rate, HRV: heart rate variability, LF Fatigue: low-frequency fatigue (combination of electrical stimulation and force sensing to measure muscle contractility and low-frequency fatigue), NIRS: near-infrared spectroscopy, sRPE: session rating of perceived exertion, SMFT: submaximal fitness testing, SSG: small-sided games, VO_2: oxygen uptake. Reproduced from Buchheit & Hader 2025.

Poor link to muscle–tendon stress

Neuromuscular load is primarily determined by forces applied to muscle–tendon units, particularly during high-intensity (eccentric) actions. GPS does not measure force, tendon strain, or fascicle behavior. As a result, metrics such as high-speed running distance or sprint counts offer only a crude approximation of mechanical stress. From a causal perspective, they fail to represent both force and repetition, which Kalkhoven et al. (2021) identify as the core ingredients of mechanical fatigue and tissue damage. Even seemingly ecological metrics, such as ground reaction forces or simple acceleration counts, can poorly reflect the actual loads experienced by specific tissues. This limitation becomes especially evident when GPS outputs are used to infer injury risk (Buchheit, Settembre et al., 2024; Jiang, 2022). Associations between running volumes and injury are often weak, inconsistent, or even paradoxical—not because injury is random, but because the metrics used are too distal from the underlying biological mechanisms (Kalkhoven et al., 2021). Crucially, this reductionist approach also ignores the multitude of interacting factors that modulate injury risk, including tissue capacity, load history, recovery status, psychological stress, technical demands, tactical context, and individual biological variability. Injury is arguably the most multifactorial and complex outcome in sport science, and expecting isolated GPS-derived variables to meaningfully predict it reflects a fundamental mismatch between measurement simplicity and biological complexity.

Poor sensitivity to eccentric work

Deceleration counts are often used as proxies for eccentric loading (Hader 2019; Harper 2019). However, the neuromuscular cost of braking depends on approach speed, braking strategy, body orientation, fatigue, and surface conditions, which GPS does not capture (Buchheit & Simpson 2017). It also depends on the athlete's eccentric strength and braking capacity: for the same external deceleration (i.e., the same mechanical "work" demand), a relatively stronger player (pound-for-pound) operates at a lower fraction of their capacity, and therefore typically incurs less relative fatigue and tissue strain. Two decelerations of identical magnitude can therefore impose different tissue loads, which is a practical reminder that improving eccentric/braking strength through targeted gym work can shift the internal cost of on-pitch demands, even when the GPS numbers look identical.

Blindness to non-locomotor neuromuscular load

Perhaps most critically, GPS is largely insensitive to non-locomotor sources of neuromuscular load (Buchheit, Manouvrier et al. 2015). Duels, tackles, jumps, contacts, upper-body actions, and isometric or quasi-isometric efforts can impose substantial neuromuscular load with limited displacement. Sessions can therefore appear "light" on GPS while being neuromuscularly demanding.

Why metabolic power fails to quantify load: linear assumptions and conceptual misplacement

The trajectory of metabolic power provides a useful cautionary tale for understanding the limitations of GPS 2.0. Originally proposed as a hybrid metric to integrate high-speed running and acceleration demands into a single indicator of energetic cost (Osgnach et al., 2010), metabolic power was conceptually attractive. It responded to a genuine practitioner need: to move beyond speed alone and aggregate multiple demanding locomotor actions into a single, interpretable construct, recognising that internal neuromuscular load in football is not driven by velocity per sec, but by repeated force production, braking, and re-acceleration.

However, while metabolic power was initially proposed to approximate locomotor-related energy demands, validation studies consistently demonstrated substantial divergence from true metabolic cost measured via indirect calorimetry. Specifically, GPS-derived metabolic power is systematically overestimated during low-speed locomotion and underestimated during shuttle running and sport-specific movements (Stevens et al., 2015; Brown et al., 2016; Buchheit, Manouvrier et al., 2015; Highton et al., 2017). Subsequent methodological rebuttals (Osgnach et al., 2016) failed to resolve these discrepancies, confirming that the limitation was not technological noise but a deeper conceptual mismatch.

The fundamental limitation lies in how metabolic power is computed. Despite its ambition to integrate demanding actions (Osgnach et al., 2010), metabolic power remains derived from speed rather than velocity, and therefore does not account for movement direction (Buchheit & Simpson 2017; Gray 2025). As a result, non-linear actions central to football are missed altogether, despite their disproportionate contribution to neuromuscular load. This is further illustrated by weak and inconsistent relationships between metabolic power and muscle activation, with marked dissociations observed between GPS-generated metabolic power and EMG during accelerating versus decelerating actions (Hader et al., 2016). This important limitation is addressed explicitly in the following section through ADI-based movement-signature and multidirectional mechanical work analyses (see section "The illusion of speed: confusing speed with velocity" below). The underestimation is compounded by GPS's inability to account for non-locomotor sources of neuromuscular load (see above). Consequently, it is not surprising that the overall metabolic power of football-specific actions is also underestimated (Buchheit, Manouvrier et al. 2015). More importantly, these validity issues exposed a broader problem that characterised much of GPS 2.0: an external locomotor descriptor was implicitly promoted into the wrong quadrant of the load–response framework. Metabolic power was increasingly interpreted as a proxy of internal metabolic load, despite lacking the capacity to capture systemic cardiopulmonary strain (where heart rate remains more informative, Buchheit, Akubat et al., 2025), or to provide the mechanical specificity required to infer internal neuromuscular load. From an injury-risk perspective, exposure to high-speed running appears more relevant than global energy expenditure, further limiting the applied value of a single aggregated "metabolic power" score.

This is not an argument that metabolic power (or GPS metrics more broadly) were "wrong." Rather, it illustrates how GPS 2.0 progressively blurred descriptive and interpretative boundaries, allowing externally derived locomotor metrics to be used as decision-making tools for overall human physiology, metabolism, readiness, and injury risk. In doing so, GPS was inadvertently displaced from its rightful position as only an external-load proxy in the upper-right quadrant of the framework. The lesson for GPS 3.0 is clear: external metrics are valuable, but only when interpreted for what they are, and not for what they were never designed to represent.

The collapse of distance-based logic in football

Modern football has become fluent in numbers and hesitant with thinking. Weekly HSR totals, sprint distances, and training-to-match ratios are now treated as reference points for "good practice" (Dawson 2024; Ravé 2020). However, this GPS 2.0 traditional distance-into-zone approach is highly limited when it comes to assessing neuromuscular load because it ignores how work is accumulated. Distance totals and speed-zone summaries treat all metres within a band as equivalent, regardless of when or in which context they occur, so two sessions can show identical HSR distances yet expose players to very different neuromuscular loads. Simply summing distances in predefined speed zones does not capture intensity peaks or action density (Buchheit, Balaña et al. 2025). In contrast, small changes around arbitrary thresholds (e.g. 19.8 vs 20.1 km/h) can shift an effort from "no HSR" to "HSR" despite similar strain.

Figure 2 shows that distance-based benchmarks describe "how much" work was done but not "how" that work was imposed on the system, i.e., the stress–repetition pattern that governs mechanical fatigue and tissue failure (Kalkhoven et al., 2021). The biological cost of football is likely driven by intensity peaks, action density, and the clustering of demanding movements, not by total meters in a speed zone. A week can "hit" a HSR target through a few match-like bursts or through long tempo runs; the GPS numbers look the same, but the underlying internal neuromuscular load does not.

When the fundamentals were overlooked

The failure of distance-based logic exposed a deeper issue: even within GPS 2.0, football rarely applied the most basic principles needed to individualise load. The key point is that "load" is only interpretable relative to the athlete: absolute outputs describe what happened, but not what it cost the player.

Matches are often analysed in absolutes because the game imposes fixed demands, because opponent benchmarking rarely comes with player capacity data, and because match data from external providers often prevents the use of relative thresholds. But if the objective is to understand load (not just describe demands), relative thresholds also make sense in matches: the same match output can represent very different strain depending on players' capacity. This "absolute-match" habit is then too easily extrapolated into training, where it becomes actively misleading.

Individualised thresholds have been repeatedly shown to improve relevance compared with absolute speed zones (Gualtieri 2023; Abt 2009; Méndez-Villanueva 2013; Rago 2020). In training, relative scaling is non-negotiable because the session is an intervention: dose should be prescribed and audited against individual capacity. In practice, systematic assessment of MAS or MSS was often absent, maximal acceleration was rarely individualised (Martínez-Cabrera 2021). Pragmatic alternatives such as %ASR (Méndez-Villanueva

2013; Rago 2020) and VIFT-based thresholds (Padrón-Cabo 2024) help, but they do not resolve the underlying limitation that distance-zone summaries ignore intensity distribution (Méndez-Villanueva 2013). Bottom line: if we want "load" rather than "locomotion," relative anchors should be the default lens in both training and match contexts.

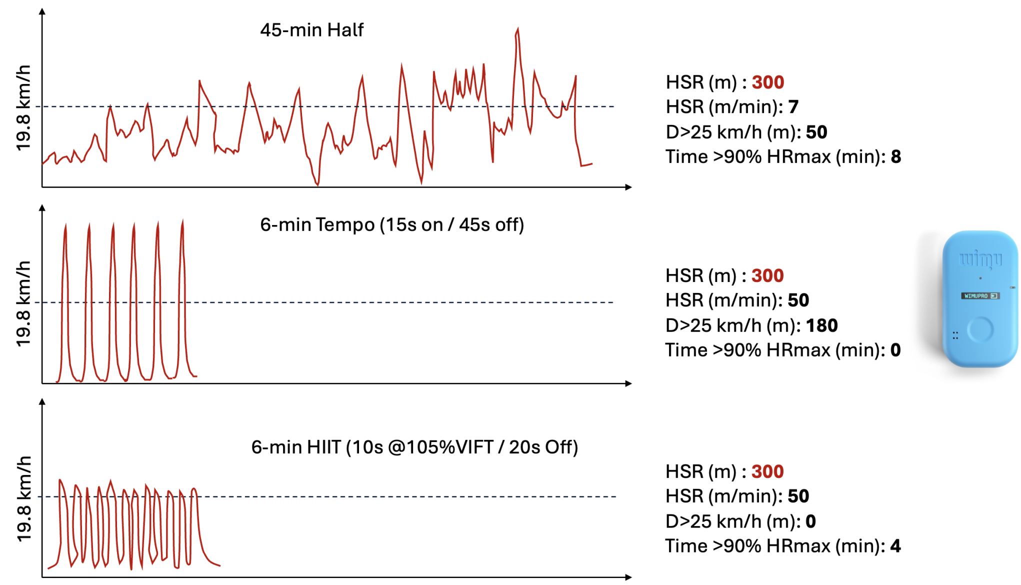


Fig. 2. Three theoretical examples of how 300 m of high-speed running (HSR, >19.8 km/h) are accumulated in different scenarios: a typical match (1st half, upper panel), a tempo run (middle panel), and a high-intensity interval training (HIIT) session (lower panel). Although the total HSR distance is identical across all three examples, the patterns of accumulation differ greatly. The match distributes HSR over 45 minutes, whereas the tempo run and HIIT session condense the same distance into just 6 minutes. This illustrates the limitations of relying solely on distance-into-zone metrics, as it overlooks the vastly different intensity and distribution of efforts. VIFT: speed reached at the end of the 30-15 Intermittent Fitness Test (Buchheit 2021). Figure Reproduced from Buchheit, Balaña et al., 2025.

Distance targets and ratio thinking: how the monster was created

For decades, training prescription in football has been guided by a clear understanding of how to manipulate volume, intensity, and recovery to target specific adaptations. In line with the dose–response concept (Impellizzeri, 2023), load metrics were historically used as checks: did the planned work align with the intended stimulus?

With GPS-derived locomotor metrics, however, this link remains largely unproven. We still lack clear evidence that most GPS variables exhibit a meaningful dose–response relationship with adaptation. Aside from a small number of relatively consistent findings (e.g., Buchheit, Settembre et al., 2024; Ellis 2021; Ellis 2022), fundamental questions remain unanswered: how much is enough, how much is too much, and what constitutes a minimum effective dose when defined by GPS rather than by performance or physiology. Importantly, while match load itself is now relatively well described (Dixon 2026), this does not explain why it became the central reference against which training is judged. The fact that something is well characterised does not make it an appropriate physiological anchor. In the absence of dose–response evidence, practice has defaulted to heuristics, with "match load" used as the de facto target to chase, through prescriptions such as "two times match demands," weekly HSR quotas, or historically derived norms (Gualtieri 2023; Ravé 2020). Notably, this logic is far from universal across team sports: in sports such as handball or basketball, training is rarely anchored to reproducing ratios of match locomotor loads, further questioning the assumption that match exposure should automatically define optimal training dose in football.

This evidence vacuum has allowed normative analysis to fill the void. What is most common has quietly become what is assumed to be optimal. As highlighted by Little & Buchheit (2025), no GPS-based normative threshold can currently be defended as an evidence-derived target; most simply mirror historical loading patterns. Distance targets, initially intended as descriptive safeguards, progressively became prescriptive goals.

The behavioural consequences of this shift are visible in the widespread use of "top-ups" (Buchheit, 2019a; 2019b; Lacome, 2018b). When sessions fail to reach predefined GPS targets, players are asked to run, often linearly and often after training, to "hit the numbers." A one-off running top-up can be preferable to not exposing players to any high-speed running at all, particularly when the objective is short-term preparation for an upcoming match (e.g., the following Saturday). In this sense, top-ups may act as a symptom-level fix, ensuring minimal exposure to key demands when football constraints (tactical focus, reduced numbers, load management, weather, or time limitations) have limited high-speed actions during the main session. The problem arises when top-ups become habitual rather than exceptional. When consistently required, they signal not good monitoring but poor session design.

Dashboards and monitoring tools are not problematic in themselves; when built on appropriate metrics and used for auditing and decision support, they can be highly relevant. However, when numerical targets become objectives rather than indicators, training logic is inverted. In such cases, top-ups may satisfy dashboards, but they remain conceptually flawed: distance becomes the goal instead of the by-product of solving football problems (Buchheit & Verheijen, Training Podcast, Episode #99). In practice, repeated top-ups are rarely additional preparation; they are a repair mechanism for suboptimal programming.

From the player's perspective, this logic can border on absurd. A tactically intelligent player may cover less ground precisely because they are positionally efficient, anticipate play, and arrive where they are needed without unnecessary displacement… yet they are "punished" with extra running for having been clever. As Raymond Verheijen has repeatedly argued, this inverts football logic: players should run to execute football actions, not play football to justify running. When good football produces less running, the correct interpretation is not 'we need more running'; it is that the football task (space, opponents, constraints) shaped the observed locomotor output.

Ratios were meant to fix this problem. Instead, they amplified it. Ratios promised context: training relative to match demands, rather than raw totals (Gualtieri 2023; Ravé 2020). Yet, as outlined by Little and Buchheit (2025), ratios carry fundamental limitations. They mathematically couple numerator and denominator, obscure absolute load, compress complex load distributions into a single value, and assume linear relationships where none exist. Ratios can change meaningfully without any real change in training content, while substantial changes in load structure may remain hidden behind a stable ratio. In effect, ratios reduce information precisely when greater resolution is required. More importantly, ratio thinking tempts staff to plan backwards from locomotor outputs (run first) rather than forwards from football problems (play first), which is exactly how top-ups and dashboard compliance take over.

It is important to acknowledge that the original logic underpinning training-to-match ratios, particularly for high-speed running (HSR), was not unreasonable (Figure 3, Buchheit 2025). In the absence of clear dose–response evidence for GPS-derived metrics, ratios were used pragmatically to maintain chronic exposure to demanding locomotor actions and to avoid large week-to-week fluctuations. From this perspective, chasing a weekly HSR training-to-match (T/M) exposure of ∼1 was at least defensible, as it aimed to stabilise tolerance to sprint-related demands rather than to optimise performance.

However, it can also be argued that even this ∼1 times match HSR reference may be too high. During congested schedules, repeated exposure to near-match loads is often associated with reduced performance (Buchheit M, Settembre et al. 2022; Settembre 2024) and increased injury risk (Dupont 2010; Jiang 2022; Pinheiro 2023). If congestion represents a context of excessive load rather than an optimal one, then systematically chasing match-equivalent weekly exposure may, paradoxically, hinder rather than sustain performance. This raises the possibility that an "optimal" training-to-match reference should sit below one full match load, rather than replicate the very conditions of a typical match load.

Furthermore, applied practice quickly exposed a fundamental inconsistency. While HSR and sprinting typically require deliberate planning to accumulate sufficient weekly exposure, accelerations and decelerations are present in almost every football session. As a result, training-to-match ratios for arbitrary +/-2 or 3 m.s-2 threshold accelerations and decelerations frequently exceed 3–4 without concern, whereas similar ratios for HSR are routinely flagged as problematic. This discrepancy raises a critical question: why would a T/M ratio of 3 be considered dangerous for HSR, but entirely acceptable (or unavoidable) for accelerations and decelerations? The answer is not physiological, but conceptual: it reflects the limitations of distance- or count-based metrics and ratio logic, rather than true differences in biological tolerance (Buchheit 2025).

In our own work (Buchheit, Settembre et al., 2024), a microcycle T/M HSR ratio of ∼0.6–0.8 was associated with lower injury rates (Figure 4). The issue is not the principle of prescribing exposure relative to match demands; when those demands are robustly and meaningfully quantified, such an approach is likely both logical and desirable. Rather, in applied settings, the ratio rapidly became a rule (i.e., flagged, chased, and manipulated), often without sufficient consideration of the limited measurement strength of GPS-derived variables. Low ratios were "fixed" with top-ups; high ratios were feared regardless of context. In this sense, the problem lies less in prescription itself than in the use of relatively weak measures to drive prescriptive decisions.

In hindsight, this is where the real monster emerged: not generic running per se, but the belief that a single distance-based ratio could meaningfully govern preparation. When ratios become targets rather than descriptors, practice drifts from preparing players to managing numbers. Compliance replaces competence, and football readiness becomes secondary to dashboard hygiene.

Figure 5 illustrates the problem. Two weeks can display identical T/M ratios while representing fundamentally different biological exposures. A ratio of ∼0.8 achieved through football-specific training likely reflects meaningful neuromuscular preparation. The same ratio reached by adding generic linear running may satisfy dashboards but deliver a very different, and often poorer, stimulus. Numerically equivalent ratios can therefore mask profoundly different neuromuscular realities (see above section "Same external load does not mean same internal neuromuscular load and Silva 2018).

More critically, figure 5 highlights the opposite paradox: a high T/M ratio (>1.5–2.0), typically flagged as "high risk," may be largely driven by generic running during the pre-season for example, and thus be less problematic than expected. The link between injuries and workload is not inherent in the workload ratio itself, but rather in the quality and context of the load that leads to that ratio. As Kalkhoven et al. (2021) point out, current approaches often rely on "generic workload math built on non-specific inputs, without any explicit representation of tissue forces, fatigue, or damage".

At a minimum, this leads to an obvious, but still inconsistently applied, best practice: generic running and football-specific running must be separated in all dashboards, reports, and ratio calculations. This distinction is not revolutionary; it is something we could—and should—have done long ago. Without it, ratios and norms remain biologically ambiguous and clinically misleading. The real question, then, is not whether players should be prepared for match demands, but how those demands are conceptualised and recreated. Start with ratios and running numbers, and you end with running solutions. Start with football problems, and the running will emerge naturally, provided the metrics used are capable of distinguishing preparation from mere accumulation.

Despite two decades of accumulated experience, football practice has remained far from meaningfully assessing neuromuscular load with GPS technology, and even further from capturing metabolic load (Figure 6). These shortcomings were not merely technological, but fundamentally conceptual. Together, they mark the end of GPS 2.0 and explain why the transition to GPS 3.0 is not optional, but necessary.

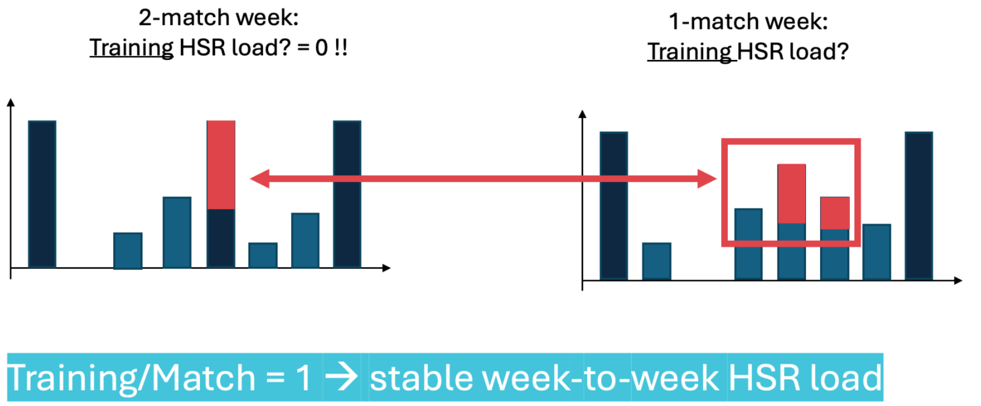


Fig. 3. **Conceptual illustration of how training-to-match (T/M) ratios have been used to suggest optimal absolute weekly high-speed running (HSR) exposure ranges when match congestion varies. In a two-match week (left panel), training HSR may approach zero (need for recovery between matches). In a one-match week (right panel), additional training HSR is required to maintain a comparable weekly load. When training HSR is adjusted accordingly, a T/M ratio close to 1 can yield a relatively stable week-to-week HSR exposure despite large differences in match schedules. This example highlights how ratios can appear "correct" while masking substantial differences in the origin, distribution, and biological meaning of the load.**

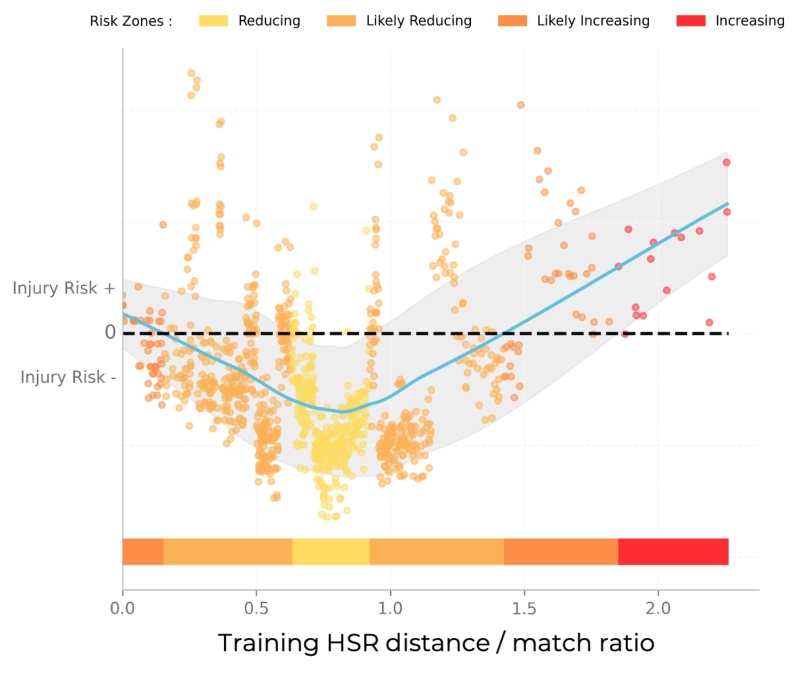


Fig. 4. **SHAP feature dependence plots for match injury risk vs. cumulated high-speed running distance (>20 km/h) during training over 6- to 8-day turnarounds (expressed as a ratio of match demands). Injury (+/-) is quantified as the magnitude of the SHAP contribution. Taken from Buchheit, Settembre et al. 2024.**

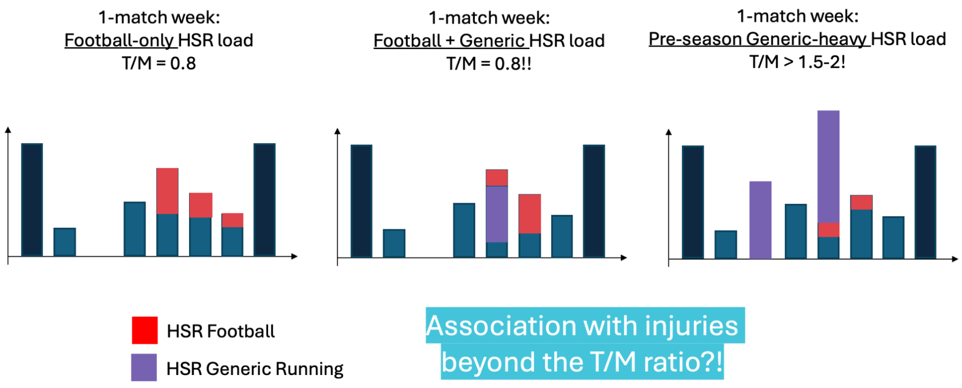


Fig. 5. Conceptual illustration showing why training-to-match (T/M) ratios alone are insufficient to interpret neuromuscular load and injury risk, and why the origin of high-speed running (HSR) matters. Left panel – Football-only HSR (T/M ≈ 0.8). All HSR exposure is embedded within football-specific activities (training and match). Although the T/M ratio aligns with ranges associated with reduced injury risk in field studies, the load reflects realistic movement variability, tactical context, and neuromuscular specificity. Middle panel – Football + generic HSR (T/M ≈ 0.8). The same T/M ratio is achieved, but through a mixed contribution of football-specific HSR and generic linear running (e.g., top-ups). Despite identical ratios, this profile likely differs biologically from the left panel, with football-specific exposure plausibly more protective due to greater coordinative, perceptual, and task-specific stimuli. Right panel – Generic-heavy HSR (T/M > 1.5–2.0). The ratio exceeds values often flagged as "high risk" in the literature; however, most HSR is derived from generic running. Despite an unfavourable ratio numerically, this profile may be less problematic than expected, as generic HSR imposes different neuromuscular and mechanical demands than football-specific actions.

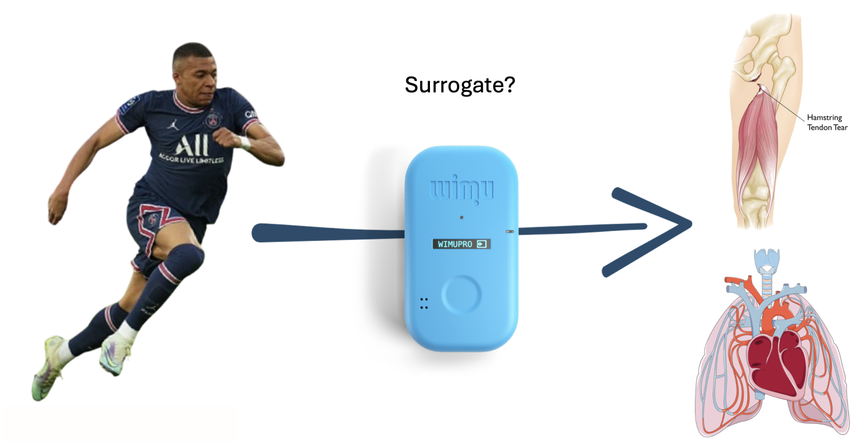


Fig. 6. Conceptual illustration of the surrogate problem in GPS 2.0. GPS-derived variables quantify external locomotor behaviour (centre), originating from player displacements (left), but are often interpreted as proxies of both neuromuscular tissue stress (e.g., muscle–tendon loading) and metabolic strain (e.g., cardiopulmonary stress; right). Such indirect proxy use requires particular caution for neuromuscular load, which is precisely the motivation for the GPS 3.0 approach, refining interpretation toward mechanically grounded, context-sensitive measures. For metabolic load, the inference is an even longer stretch: a substantial proportion of energy expenditure arises from non-locomotor sources (e.g., isometric actions, contacts, upper-body work, tactical behaviours) that GPS cannot capture. Consequently, traditional GPS 2.0 outputs (distances, speed zones, ratios) sit firmly in the external-load quadrant and should not be used as direct indicators of internal neuromuscular or metabolic stress.

GPS 3.0: what better GPS analysis should look like

The limitations of traditional GPS metrics do not imply that neuromuscular load cannot be informed by tracking technology. Improvements in hardware (i.e., higher sampling frequencies, better sensor stability, and improved inter-unit reliability; Bataller-Cervero 2019; Gimenez 2020; Hoppe 2018) have addressed several historical criticisms (Buchheit 2014) and will continue to refine data accuracy. But improved sensors will not resolve conceptual misinterpretation. The core problem is not the quality of the data collected, but the way those data are interpreted. Current GPS practices remain conceptually misaligned with the mechanical and neuromuscular realities of football. The transition to GPS 3.0 therefore depends far less on upgrading hardware than on applying better physics, better context, and better intelligence to the data we already have.

The illusion of speed: confusing speed with velocity

At the core of current GPS practice lies a flawed premise: that speed is the primary indicator of intensity. This assumption has driven the dominance of linear metrics such as total distance, high-speed running, and sprint distance. While convenient, these variables are poorly suited to multidirectional sports such as football, where frequent accelerations, decelerations, and changes in direction impose much higher mechanical and neuromuscular loads than constant- and linear-speed running (Buchheit & Simpson 2017; Gray, 2025; Griffin 2021; Hader 2016; Harper 2019).

The root of this issue is a basic misunderstanding of physics: the conflation of speed and velocity (Gray, 2025). Speed is scalar describing magnitude only, whereas velocity is a vector that includes both magnitude and direction. In physics, any change in velocity, whether due to a change in speed, direction, or both, is an acceleration.

Traditional GPS metrics capture acceleration almost exclusively through changes in speed, while largely ignoring acceleration arising from directional change. This omission is substantial rather than marginal. In multidirectional sports, changes in direction account for a large proportion of the mechanical work performed during meaningful football competitive actions, estimated at around one-third of total work (Gray, 2025). As a result, GPS metrics systematically underestimate the neuromuscular demands of the very movements that define football: cutting, twisting and/or braking.

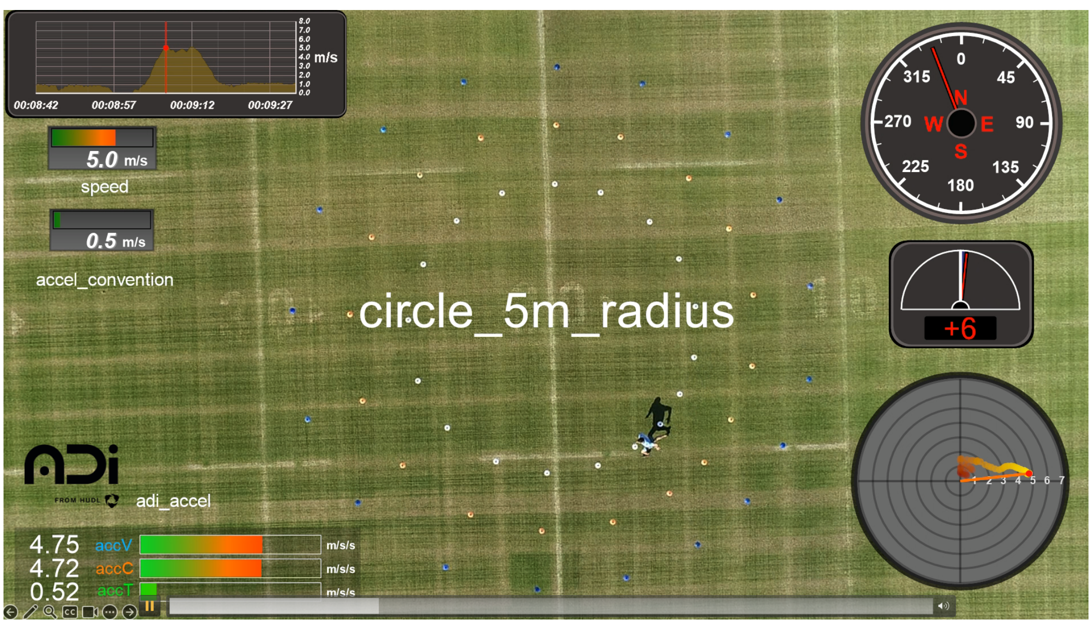


Fig. 7. Limitations of conventional GPS acceleration metrics versus direction-sensitive approaches. Conventional processing quantifies acceleration mainly from speed change and treats straight-line and curved running at the same speed as equivalent. ADI-derived acceleration incorporates the full acceleration vector, including centripetal components during curvilinear motion, capturing higher mechanical demand during curved and multidirectional actions. ADI: Athletic Data Innovation (ADI), Hudl. accV: resultant acceleration; accC: centripetal acceleration; accT: tangential acceleration. Video: `https://youtu.be/fkQkIrnmxeM`.

Why linear speed thresholds fail in multidirectional sports

From a mechanical perspective, traditional GPS metrics imply that running in a straight line at 5 m·s^{-1} is equivalent to running in a circle at the same speed (Figure 7). In physics, acceleration is fundamentally defined as the rate of change of the velocity vector, which means a change in either its magnitude (speed), direction, or both, results in acceleration. This principle is a cornerstone of classical mechanics, stemming from Newton's second law of motion (Benson 2006). The curvilinear running requires a constant change in the direction of the velocity vector, despite the fact that the speed remains constant, leading to an acceleration requiring additional force application, and resulting in increased muscle-tendon loading (Pietraszewski 2021).

Because direction is ignored, both actions are treated as equivalent by speed-based metrics. Consequently, the high forces and mechanical stress imposed by turns, cuts, and curved accelerations and decelerations (actions most associated with fatigue and injury risk) are either missed or substantially underestimated. This highlights a central limitation of GPS 2.0: it measures what is easy to quantify, not what is most relevant (Buchheit & Simpson 2017; Gray, 2025). This limitation is also industrial. Practitioners cannot directly measure true mechanical work or multidirectional loads without appropriate algorithms and tools. To our knowledge, ADI is currently the only system explicitly accounting for these components, while attempts to reproduce mechanical work with standard GPS pipelines have failed in applied contexts. Responsibility therefore also lies with the sport technology industry, which has prioritised higher sampling frequencies over genuine advances in modelling multidirectional mechanics. A true evolution toward GPS 3.0 requires stronger R&D focused on measuring mechanical work itself, not refining linear proxies.

Complete acceleration and true mechanical work

A key advancement within GPS 3.0 and the integration of the ADI analyzer is the capture of complete acceleration (Figure 7), defined as the combination of acceleration due to changes in speed and acceleration due to changes in direction (Buchheit & Simpson 2017; Gray, 2025). Ignoring directional acceleration makes it impossible to quantify true mechanical work and undermines attempts to link external load to conditioning, recovery, or injury risk.

By accounting for complete acceleration, power-based models align GPS outputs more closely with the mechanical stresses experienced by the musculoskeletal system. This is particularly relevant in football, where high-intensity actions are rarely linear and often occur under substantial perceptual and tactical constraints.

Re-establishing intensity through mechanical power

If speed alone is insufficient to characterise neuromuscular demand, then intensity itself must be redefined. In multidirectional sports such as football, mechanical work (MW) and mechanical power (MP) provide a more physiologically and mechanically grounded representation of intensity than speed or distance alone. MW (expressed in kJ) quantifies the total mechanical volume of work performed, whereas MP (expressed in $\mathrm{W{\cdot}kg^{-1}}$) represents the rate at which this work is produced, and therefore intensity. Importantly, these constructs are not competing metrics but two expressions of the same phenomenon, differing only by their units and temporal normalisation. Indeed, when MW is expressed per unit of time (e.g., $\mathrm{kJ{\cdot}min^{-1}}$), it becomes an intensity metric analogous to MP. A further practical advantage is that MP is inherently a relative metric ($\mathrm{W{\cdot}kg^{-1}}$): it scales mechanical output to body mass, which means that player build and "cost of moving mass" become more visible in the monitoring signal, much like in cycling. In other words, two players can produce similar absolute work, yet the heavier player may operate at a higher relative mechanical cost, with implications for fatigue and resilience that depend on individual morphology and composition (e.g., the distribution of lean mass, bone density, and muscle density). This does not imply that "lighter is always better," but it does reinforce why strength-to-mass ratio and mechanical efficiency matter: in some cases, reducing non-functional mass (even if lean) could plausibly improve movement economy and durability without compromising performance, provided force-production capacity is maintained.

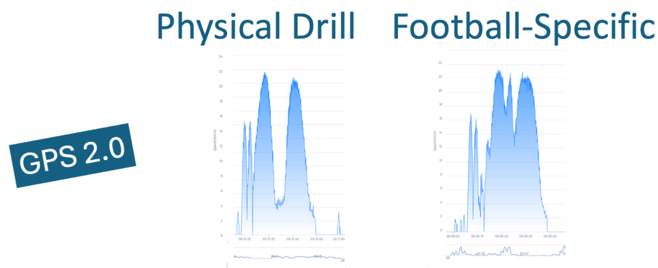
No dedicated reliability studies have examined MW- or MP-derived metrics in football. Their error is constrained by the reliability of the underlying measurements (speed and the full acceleration vector) (Bataller-Cervero 2019; Gimenez 2020; Hoppe 2018). Because MW/MP use the resultant acceleration vector, axis-specific random noise may partially cancel rather than accumulate. There is therefore no theoretical reason to expect MW/MP to be less reliable than conventional acceleration-based metrics (Gray 2025). The key advantage of power-based approaches is that they integrate force and velocity and account for the effort required to change both speed and direction (Figure 7, Gray, 2025). By incorporating the full acceleration vector (including tangential and centripetal components) mechanical work and power quantify true mechanical demand, rather than linear displacement. This allows the most intense periods of training and competition to be identified with greater fidelity, particularly in sports where peak demands are driven by repeated accelerations, decelerations, and changes of direction rather than by straight-line sprinting alone. As a result, positional or role-specific demands that are often obscured by high-speed running (HSR) metrics (such as those of central midfielders) become more visible and interpretable.

A practical implication of treating mechanical work/power as "unifying" constructs is that MW should rarely be reported as a single undifferentiated total. In football, similar total MW can be produced through very different locomotor solutions (e.g., dense acceleration–braking sequences vs stride-dominated high-speed running), with different neuromuscular consequences. Splitting MW therefore helps answer a more informative question: what type of mechanical work did the player actually perform, and how was it produced?

There are multiple valid ways to partition the "source" of MW, depending on the purpose. A movement-pattern lens can separate work into linear vs curvilinear/change-of-direction components, which is useful to profile how actions are expressed and how constraints shape movement signatures (Figures 8 and 9). A tissue-/muscle-loading lens can instead separate MW into a high-speed running stride-dominant component ($\mathrm{MW_{stride}}$) and an acceleration/braking/change-of-direction component ($\mathrm{MW_{thigh}}$), which is often more directly aligned with practitioners' interest in neuromuscular loading. Both perspectives are valuable; in this manuscript we prioritise $\mathrm{MW_{thigh}/MW_{stride}}$ because it provides a more interpretable bridge toward internal neuromuscular load, while acknowledging that the terminology is not perfect (e.g., "thigh" implies a muscle-group emphasis whereas "stride" describes a movement pattern, even if it plausibly reflects long-length hamstring loading and substantial plantar-flexor elastic work).

More precisely, while $\mathrm{MW_{thigh}}$ is calculated as the sum of all linear and multidirectional accelerations, decelerations, and directional changes, $\mathrm{MW_{stride}}$ represents the work produced during stride-dominated high-speed running, including both straight-line and curvilinear (constant-speed) running where substantial centripetal acceleration may be present. With hindsight, any operational split that treats stride work as purely linear (i.e., ignoring curvilinear high-speed running) is incomplete because curved high-speed running can generate substantial centripetal forces and mechanical work despite relatively stable speed. Consequently, part of the neuromuscular cost of sprinting actions can be underestimated if these curvilinear contributions are not appropriately captured.

Finally, for clarity and continuity with earlier work: in several earlier publications (e.g., Buchheit & Simpson 2017; Lacome 2018a, 2018b & 2018c), we used the term "mechanical work" to refer specifically to what we now label $\mathrm{MW_{thigh}}$—i.e., the acceleration/deceleration and change-of-direction contribution—while the stride-dominated component was intentionally treated separately and therefore largely excluded from that construct. The underlying idea was consistent; the terminology is now made explicit.



TD (m)	113	113
HSR (m)	50	60
Top Speed (km/h)	24	24
Max Acc (m/sec2)	4.7	5
#Acc	3	3
Max Dec (m/sec2)	5	4.8
#Dec	2	2

Fig. 8. Comparison of a generic physical drill (large and close views) and a football-specific drill (large and close views) showing similar values for conventional GPS outputs (total distance, high-speed running distance, peak speed, acceleration and deceleration counts). Despite near-identical summary metrics, the velocity profiles illustrate different intensity distributions over time, highlighting how traditional GPS variables can mask substantial differences in movement structure and mechanical demands between generic and football-specific activities.

Total Mechanical Work (Kj)	14	20
Linear MW (Kj) (GPS 2.0 legacy)	9	6
Non-linear MW (Kj) (GPS 3.0 advances)	5	14
Part of the true total MW missed by typical GPS 2.0 linear-only analyses	5/14 = 30%	14/20 = 70%

ADi FROM HUDL

Fig. 9. Movement-signature (radar illustration) and mechanical work analysis of the same generic running physical drill (large and close views) and a football-specific drill (large and close views) presented in Figure 8. Radar plots show the distribution of manoeuvre types (e.g., linear accelerations/decelerations, constant-speed turns, curved actions). Each dot represents a single action, expressed in m·s^{-2}, and the percentage shown on each axis corresponds to the proportion of time spent in multidirectional acceleration for that session, drill, or manoeuvre. While total MW (kJ) is higher in the football-specific drill, this difference is driven predominantly by a much larger contribution of non-linear, multidirectional and non-linear work, whereas the physical drill is largely dominated by linear actions. The table quantifies total MW and its linear vs. non-linear components, illustrating how analyses that rely mainly on linear estimates (e.g., linear accelerations/decelerations and HSR only) miss a substantial proportion of the true mechanical work, approximately 30% in the physical drill and ~70% in the football-specific drill. This example highlights how movement-signature analysis (Athletic Data Innovation, ADI; Hudl) and explicit separation of linear and non-linear MW uncover neuromuscular demands that remain largely invisible with traditional GPS summary metrics.

From raw data to movement signatures

A defining feature of GPS 3.0 is the shift from reporting isolated variables to analysing movement signatures. Advanced analytical approaches demonstrate that the same raw GPS data can be used to detect and classify meaningful manoeuvres, both linear and multidirectional, rather than merely summing distances (Gray, 2025). In this context, a movement signature is the distribution and sequence of locomotor events an athlete produces, described from the full acceleration vector rather than from speed alone. Radar-type "compass" plots (Figure 9) place each manoeuvre family (for example, linear accelerations, decelerations, constant-speed turns, curved high-speed runs, and thigh multidirectional cuts) into specific angular sectors, with the radius showing the relative contribution (time, count, or mechanical work) of each event type. This representation makes visible which kinds of manoeuvres dominate a drill or session, how often players brake versus accelerate, how much work occurs on curves versus straight lines, and on which side and orientation these actions occur (for example, right vs left, forward vs backward displacements). Movement-signature analysis therefore focuses on how intensity is produced, structured, and sequenced across these actions. It provides insight not only into how much work is performed, but how it is executed and under which mechanical constraints.

Crucially, such approaches allow contextual differentiation. A generic running physical drill (large and close views) and a football-specific drill (large and close views) can produce similar GPS totals (Figure 8), but may reveal entirely different movement signatures and MW/MP profiles when examined through a pattern-based lens (Figure 9), which often aligns more closely with practitioners' qualitative impressions of session difficulty, internal neuromuscular load, and football specificity.

From distance to peak high-intensity periods

Cumulative running distance is a poor measure of neuromuscular damage because the stress imposed on tissues does not scale linearly with distance covered (Edwards 2018; Kalkhoven 2021). The true mechanical challenge for muscle-tendon structures is the magnitude of the stress, rather than the cumulative number of loading cycles.

Biological tissues exhibit an inverse power-law behavior, meaning a minor increase in peak stress dramatically reduces the number of safe loading cycles. This explains why high-intensity actions require significantly fewer repetitions to cause tissue damage compared to low-intensity activities (Figure 10, Edwards 2018; Kalkhoven 2021).

Injury risk appears to be disproportionately linked to brief periods of very high internal neuromuscular load, such as maximal sprinting or intense multidirectional movements, according to the stress–life relationship (Figure 10). In these critical scenarios, the intensity and duration of these short, high-intensity efforts are the key factors, not the overall training volume or cumulative distance covered over a season. This perspective aligns more closely with fatigue-based models of tissue failure, which posit that cumulative damage depends on the complete loading pattern (stress magnitude multiplied by repetitions), unlike simple session-level distance totals (Figure 8).

Expressing GPS-derived load as per-minute metrics (e.g. m·min^{-1}, accelerations·min^{-1}) has long been standard practice in football (Varley 2012). While useful for broad comparisons, these metrics are fundamentally limited when examined at the session level, as they inherently include rest periods, stoppages, and hydration breaks. As a result, they provide little meaningful information about true mechanical intensity.

To address this, practitioners commonly analyse load at the drill level, reporting average intensities over fixed durations (e.g. 2 accelerations·min^{-1} during a 4-min small-sided game). Although this approach improves contextual relevance, it remains an average and therefore masks short, high-intensity passages that may be most relevant for internal neuromuscular load. In practice, brief bursts of extreme demand can be diluted by lower-intensity phases within the same drill.

This limitation prompted a shift toward analysing rolling averages over shorter time windows, allowing the identification of transient peaks in intensity rather than relying on cumulative session or match values (Varley et al., 2012). This approach, later formalised as peak intensity periods (Buchheit & Mayer, 2019; Buchheit, Sandua et al. 2023; Delaney 2017; Lacome 2018b), also termed Most Intense Periods (MIPs) or Most Demanding Periods (MDPs) (Rico-González et al., 2021; Lino-Mesquita et al., 2025), has consistently been shown to better approximate mechanical demands than aggregated metrics. These are typically assessed over short rolling windows (e.g. 30 s, 1, 3, or 5 min), and capture when (extreme) mechanical stress occurs, rather than simply how much work is accumulated.

Importantly, this concept of peak demands is not new. Research using rolling averages to identify the most demanding passages of play was already available more than a decade ago (Delaney 2017; Lacome 2018b; Varley et al. 2012). Yet, despite this evidence, adoption by practitioners has been slow, with most applied reviews and frameworks only embracing MIPs around 2020 (Rico-González et al., 2021; Lino-Mesquita et al., 2025). This delay cannot be attributed to technological or methodological limitations: peak-demand analysis required no new sensors, higher sampling rates, or novel metrics, but only a different way of interrogating existing GPS data.

This gap exemplifies a core limitation of the GPS 2.0 era: the issue was not what could be measured, but how data were interpreted. GPS 3.0 builds on this lesson by integrating peak-demand analysis with mechanically informed metrics to move beyond cumulative volume toward a more biologically plausible representation of internal neuromuscular load. Evidence from elite football supports this framework (Figure 11), indicating that the immediate match-specific demands, rather than cumulative match loads, are associated with injury risk. Specifically, studies have shown that players who incurred injuries had greater sprint exposure during the minute (Gregson et al., 2020) and 5-minute (Moreno-Pérez et al., 2024) periods immediately preceding the injury. Moreno-Pérez et al. (2024) observed higher sprint distances in these intense, pre-injury time windows, a difference that was not evident when considering the total match load.

Peak periods as a priority metric in return-to-performance

Importantly, also in the context of injured players, since players often return as substitutes, building full match-volume capacity may not be the most pressing objective of rehabilitation. Players can, however, face high-intensity bursts even during a 20-minute appearance, so preparing them to tolerate the most intense periods over shorter durations (e.g., 1, 3, or 5 min) should be a priority. A few examples of load progression and associated GPS metrics for different scenarios are shown elsewhere (Buchheit & Mayer, 2019; Buchheit, Balaña et al. 2025), with targets provided in terms of both volume and MIPs.

Together, these findings illustrate why intensity-based metrics such as peak periods or MIPs offer a more mechanistically defensible approach than distance-based thresholds when the objective is to understand internal neuromuscular load and injury-relevant loading in football.

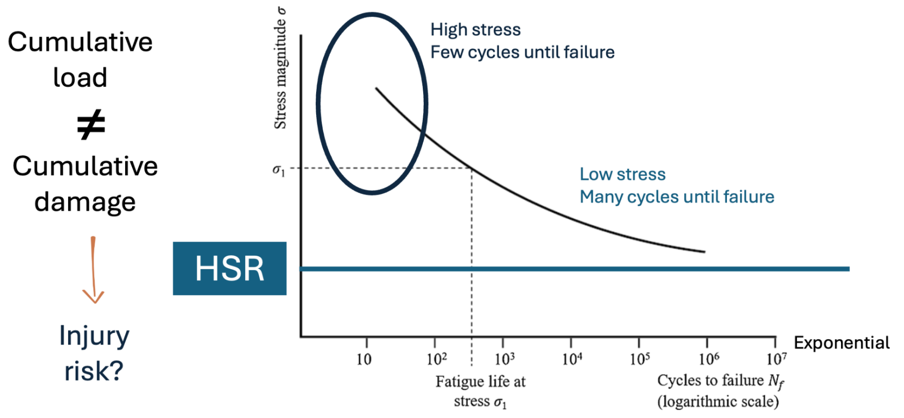


Fig. 10. **Conceptual stress–life (S–N) relationship illustrating the non-linear link between mechanical load magnitude and tissue damage, adapted from Kalkhoven et al. (2021) and Edwards (2018). Stress magnitude (σ) represents the intensity of neuromuscular loading, while cycles (N) refer to discrete repetitions of mechanical loading applied to the muscle–tendon–bone unit (e.g., sprint strides, accelerations, decelerations, or changes of direction). High-magnitude loads require relatively few cycles to induce damage, whereas lower-magnitude loads must be repeated many times to reach a comparable failure threshold. This framework explains why short exposures to very high mechanical intensity may contribute disproportionately to injury risk, and why cumulative distance-based metrics have limited relevance for estimating neuromuscular damage.**

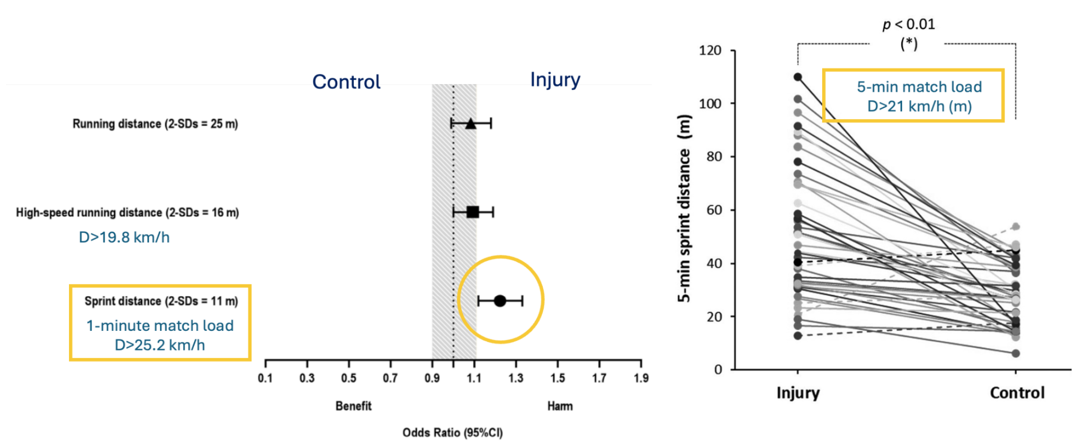


Fig. 11. **Association between sprint exposure and injury occurrence in elite football. Data from Gregson et al. (2020) (left) show that players who sustained an injury accumulated greater sprint distance during the 1-minute period preceding injury compared with their own non-injury match periods. Similarly, Moreno-Pérez et al. (2024) (right) report higher sprint distances during the 5-minute match windows prior to injury. Notably, these associations were observed for 1-min peak-intensity periods rather than cumulative match loads, supporting the relevance of intensity-based metrics over distance-based measures for understanding injury-relevant internal neuromuscular load.**

From multiple peak metrics to a coherent mechanical framework

From a practical perspective, the move away from multiple, metric-specific MIPs is driven not only by the need to limit metric proliferation (e.g. separate MIPs for total distance, accelerations, decelerations, high-speed running; Delaney 2017; Lacome 2018b; Varley et al. 2012; Novak et al., 2021), but also by the simple reality that using several MIPs simultaneously is operationally complex and conceptually fragile. Different peak metrics are not equally constraining and are highly sensitive to training mode and conditioning status. For example, a 1-min HSR MIP of ∼40–50 m·min^{-1} (typical of match play) can be trivially exceeded during generic run-based conditioning, where values >120 m·min^{-1} are routinely achieved (Lacome 2018b). In such cases, the HSR match MIP itself loses any conditioning or neuromuscular relevance, while ignoring the fact that, within the same minute, players in football contexts also perform accelerations, decelerations, and changes of direction that fundamentally shape the mechanical demand.

This illustrates why examining isolated MIPs (e.g., HSR) is problematic: football load never arises from a single movement pattern, and attempting to combine multiple metric-specific MIPs in parallel quickly becomes impractical. What matters is keeping comparable demands together and anchoring peak references to football-specific actions rather than to generic running outputs. In practice, drills are conceived from the football task itself, with GPS then used to check whether the intended combination of match-like peak demands is effectively reproduced within the same time window, rather than to maximise any single variable in isolation.

Accordingly, a more parsimonious and meaningful approach is to prioritise peak periods or MIPs derived from mechanical work (MW·min^{-1}) or mechanical power (MP), which integrate both linear and multidirectional actions, and better reflect the mechanical determinants of overall neuromuscular load (Buchheit & Simpson 2017; Gray, 2025) (Figure 12). Using MP-based MIPs substantially reduces metric complexity while preserving specificity. At a minimum, two complementary expressions remain necessary: one capturing MW generated through repeated accelerations, decelerations, and changes of direction ("thigh work"), and one capturing MW generated through high-speed, stride-dominated running ("stride work") (Figure 13).

Figure 12 shows that elite football players reach peak 1-min external mechanical power values of ~7–9 W·kg^{-1} when all locomotor actions are integrated. When benchmarked against cycling standards, where ~7.5–8 W·kg^{-1} is considered moderate, ~8–8.5 W·kg^{-1} good and ~8.5–9 W·kg^{-1} very good for trained cyclists over ~1 min (Johnstone 2018), these values place elite footballers in a comparable high-power range despite the very different locomotor and mechanical constraints of the sport. This comparison highlights that short-duration mechanical power demands in football are substantial and reinforces the relevance of peak power–based metrics for characterising neuromuscular intensity beyond distance or speed alone.

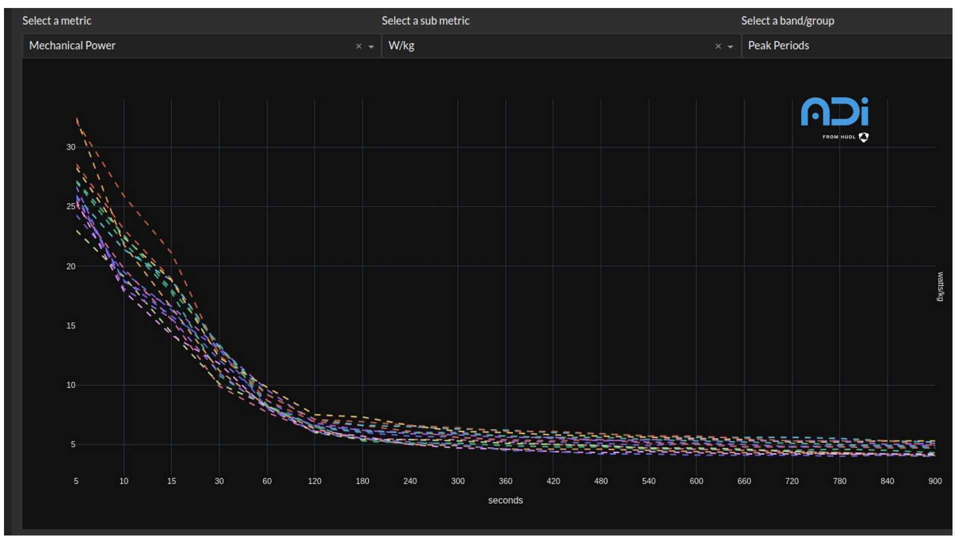


Fig. 12. Peak mechanical power–duration relationship derived from GPS data (ADi) in an elite European football squad. Curves represent the maximum rolling-average mechanical power (W·kg^{-1}) integrating straight-line running, accelerations, decelerations, and changes of direction attained across a range of time windows (from 5 s to 15 min) during a mix of training sessions and competitive match play. Each dashed line corresponds to an individual player's peak mechanical power values, illustrating the progressive decline in sustainable external mechanical power as averaging duration increases. The value at 60 s represents the peak 1-min average mechanical power (approx. 7-9 W·kg^{-1}).

From peak intensity to training dose: introducing Intensity Exposure Time (IET)

From match peaks to maximal physiological capacity: redefining the intensity reference

If internal neuromuscular load is driven primarily by intensity rather than volume (Kalkhoven 2021), monitoring frameworks should reflect this reality. One practical evolution within GPS 3.0 is the introduction of Intensity Exposure Time (IET), which shifts the focus from distance accumulation to time spent at high mechanical load levels along the stress–strain continuum, rather than within arbitrary speed bands.

IET quantifies the cumulative time spent above a relative intensity threshold (e.g., 80–90% of match-derived MIPs; Mandorino 2024), instead of the distance accumulated within predefined speed zones. Conceptually, this mirrors cardiovascular monitoring, where load is expressed as time spent above a percentage of an individual maximum (e.g., %HRmax; Buchheit, Akubat et al. 2025), but applied here to external neuromuscular intensity rather than metabolic strain.

Several reference options exist. Expressing IET relative to match-derived MIPs (Mandorino 2024) is conceptually attractive when the objective is to prepare players for competition, i.e., to expose them to intensities similar to those encountered during matches. This approach is also pragmatically appealing, as it does not require direct assessment of players' physical capacities, relying solely on match monitoring data. However, defining and operationalising match MIPs remains problematic. Match MIPs show substantial variability between games (Novak et al. 2021) and are strongly influenced by contextual factors such as tactics, opposition, scoreline, and player role. As a result, they are unstable references when the aim is to infer cumulative internal neuromuscular load rather than to describe match demands.

When IET is referenced to match-derived MIPs, the reference is context-dependent. Match MIPs vary with tactics, opposition, scoreline, role, and substitutions (Riboli 2021; Novak et al. 2021). As a result, the same relative threshold (e.g., 70% of match MIP) corresponds to different absolute intensities across teams and players. Table 1 illustrates how this inflates between-team dispersion in thresholds and IET values, limiting biological interpretability.

In addition, the method used to define MIPs directly shapes their numerical value. Whether MIPs are defined as a single all-time match peak, the average of a subset of highest match peak values (Mandorino 2024), or a mean across selected matches leads to materially different reference points (Figure 14). This methodological sensitivity further contributes to the dispersion observed in Table 1 and reinforces the idea that match-derived MIPs are highly context-dependent rather than capacity-based. These sensitivities reinforce the recommendation that match MIPs should not be treated as fixed benchmarks, but rather as "evolving reference ranges that help contextualise training design" (Lino-Mesquita et al. 2025).

More fundamentally, match MIPs do not represent a player's true maximal locomotor capacity, but merely the (highly variable) highest demands encountered within a specific competitive context (Buchheit, Mendez-Villanueva et al. 2010a; Mendez-Villanueva et al., 2011; Byrkjedal et al., 2024). As such, while match MIPs are valuable for describing competition demands, they cannot be interpreted as a measure of neuromuscular load capacity, nor should they be used as a stable intensity anchor for IET when the objective is load quantification. In this context, reliance on match MIPs introduces substantial noise, conflates context with capacity, and severely limits comparability across teams, environments, and seasons, as clearly illustrated by the wide dispersion of thresholds and IET values in Table 1.

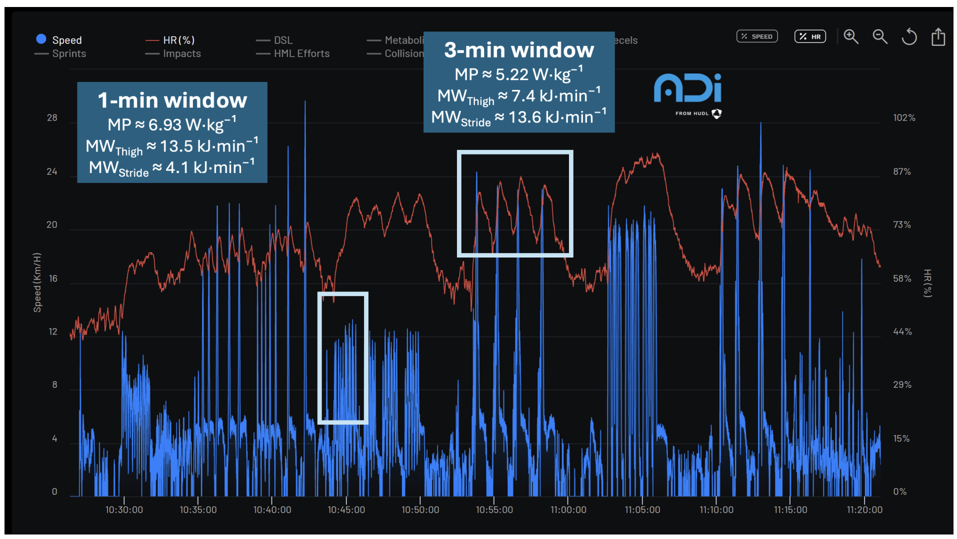


Fig. 13. Time-series data from a rehabilitation training session showing speed (blue) and heart rate (red), with mechanical power (MP) and mechanical work (MW) Most Intense Periods (MIPs) computed over different rolling windows. For each window, MW is decomposed into its stride-dominated component (MW_{stride}) and thigh, multidirectional accelerations, decelerations and changes of direction components (MW_{thigh}). A short 1-min window captures brief, very high-intensity bursts (e.g., MP $\approx$ 6.9 W$\cdot$kg^{-1}), with a relatively greater contribution from MW_{thigh}, reflecting dense sequences of accelerations, decelerations, and changes of direction. A longer 3-min window smooths these peaks and identifies a lower but more sustained intensity (e.g., MP $\approx$ 5.2 W$\cdot$kg^{-1}), with a comparatively larger MW_{stride} contribution, reflecting sustained running phases. This example illustrates that MIPs are window-dependent and that shorter windows are more sensitive to acute internal neuromuscular load, whereas longer windows better represent sustained high-load phases, while the MW_{thigh} vs MW_{stride} balance provides additional insight into the nature of the mechanical demands.

From match peaks to capacity-based intensity anchors

When the objective is to quantify load, anchoring intensity to match data is not only highly impractical, but more importantly, also conceptually unsound. Match activity is inherently constrained by context, i.e., tactical role, playing position, ball involvement, scoreline, substitutions, and the continuous requirement to execute football actions (Riboli 2021). Consequently, players rarely approach their true maximal mechanical capacity during competition (Buchheit, Mendez-Villanueva et al. 2010a; Mendez-Villanueva et al., 2011; Byrkjedal et al., 2024). Match peaks therefore describe what the game permits, not what the player can produce, making them a poor reference for load quantification.

This limitation persists even when the stated aim is to "prepare for match demands." Training players only to the intensities they typically express in competition effectively prepares them below their capacity. Over time, this leads to systematic under-loading, insufficient overload, and a gradual decline in physical fitness, particularly for players whose match roles inherently restrict high-intensity expression. In this sense, preparing for the match can paradoxically mean under-preparing the player (Little & Buchheit 2025).

A more coherent solution, and a key proposition of this manuscript, is to anchor intensity to an individual, capacity-based reference, analogous to maximal heart rate in cardiovascular monitoring. Internal load is not interpreted relative to match peak heart rate, but against a player's true maximal heart rate (Buchheit, Akubat et al. 2025). Applied to locomotion, this logic supports the use of a maximal 1-min mechanical power (or work rate; Maximal MP_{1min}) as the reference. This value reflects a player's true locomotor capacity, independent of tactical and situational constraints, and aligns with foundational work on human speed and power limits (Bundle, 2003; Figure 15). Anchoring intensity in this way provides a more stable and physiologically coherent basis for expressing relative intensity and calculating IET, while avoiding the systematic underestimation inherent to match-based references.

Importantly, this logic is not entirely new. GPS 2.0 successfully applied individualisation for sprint exposure, where intensity is expressed relative to each player's maximal sprinting speed (MSS) rather than absolute thresholds (Buchheit & Mendez-Villunueva 2010b; Buchheit & Settembre 2023; Haugen 2014). However, this principle has remained largely confined to sprint counts and sprint distance, and has not been extended to the broader locomotor spectrum, nor to the intensity or density of short peak periods, which are likely most relevant for overall internal neuromuscular load.

Table 1. Intensity thresholds (70 and 80% individual peak match MIPs) and Intensity Exposure Time for key GPS variables during matches, when considering match MIPs of 1 min. For comparison with Mandorino 2024, the two Ligue 1/champions league clubs and Sepsi OSK match reference MIPs were defined as the average of the peak intensities recorded across various matches. Values are provided as mean (SD). Only full matches data included.

Source	Variable	MIP	60% Threshold	Time above 60% Threshold (min)	70% Threshold	Time above 70% Threshold (min)	80% Threshold	Time above 80% Threshold (min)
Parma FC, 1st Italian League, 31 players, avg 10 matches per player.	TD ($m \cdot min^{-1}$)	192.2 ± 12.2					153.8	6.4 ± 3.5
	HSR ($m \cdot min^{-1}$)	56.3 ± 4.6					45.0	1.3 ± 1.1
Club 1, French Ligue/ UEFA Champions League, 14 players, avg 4 matches per player.	TD ($m \cdot min^{-1}$)	193.7 ± 12.9	116.2	32.1 ± 5.2	135.5	13.3 ± 6.2	155.0	6.1 ± 3.2
	HSR ($m \cdot min^{-1}$)	52.2 ± 14.5	31.3	4.2 ± 2.3	36.5	2.6 ± 1.3	41.8	1.9 ± 0.9
	Acc+Dec ($\# \cdot min^{-1}$)	3.9 ± 1.7	2.3	6.8 ± 2.1	2.7	5.9 ± 1.8	3.1	3.5 ± 0.5
	Mechanical Power ($W \cdot kg^{-1}$)	7.3 ± 0.7	4.3	20.2 ± 5.7	5.1	10.2 ± 5.9	5.9	4.4 ± 1.0
Club 2, French Ligue/ UEFA Champions League, 10 players, avg 5 matches per player.	TD ($m \cdot min^{-1}$)	186.1± 13.1	111.7	44.1 ± 4.3	130.3	25.5 ± 3.0	148.9	10.8 ± 2.3
	HSR ($m \cdot min^{-1}$)	56.4 ± 8.8	33.8	1.9 ± 0.7	39.5	1.0 ± 0.3	45.1	0.5 ± 0.4
	Acc+Dec ($\# \cdot min^{-1}$)	6.6 ± 1.3	4.0	8.4 ± 3.7	4.6	4.4 ± 2.3	5.3	3.0 ± 1.1
	Mechanical Power ($W \cdot kg^{-1}$)	6.7 ± 0.5	4.0	31.3 ± 3.6	4.7	16.9 ± 2.6	5.4	7.4 ± 1.3
Sepsi OSK, Romanian 2nd League, 12 players, avg 4 matches per player.	TD ($m \cdot min^{-1}$)	187.0 ± 7.9	112.2	27.4± 8	130.9	12.8 ± 5.8	149.6	5.9 ± 2.3
	HSR ($m \cdot min^{-1}$)	41.6 ± 4.1	25	3.4± 1.3	29.1	2.3 ± 0.8	33.3	1.3 ± 0.7
	Acc+Dec ($\# \cdot min^{-1}$)	6.3 ± 0.84	3.8	4.1± 1.4	4.4	3.5 ± 0.4	5.0	1.5 ± 0.5
	Mechanical Power ($W \cdot kg^{-1}$)	6.4 ± 0.88	3.81	18.1 ± 1.2	4.44	5.6 ± 1.4	5.1	3.2 ± 1.6

Estimation of maximal 1-min all-out mechanical power capacity

Maximal MP_{1min} capacity can be estimated using the speed–duration framework proposed by Bundle (2003) (Figures 15 and 16). This model describes maximal running performance across durations from a few seconds to several minutes using two measurable speed limits: 1) MSS, representing a player's maximal sprinting speed supported by neuromuscular factors, force application capacity and running technique, and 2) maximal aerobic speed (MAS), representing the maximal speed supported by aerobic power. The difference between these two speeds defines the anaerobic speed reserve (ASR).

Bundle and Weyand demonstrated that maximal running speed declines exponentially with effort duration, with a time constant (Figure 15, $k \approx 0.013\ s^{-1}$). When averaged over a 60-s effort, this relationship indicates that the maximal mean speed sustainable for 1 min (Estimated Maximal S_{1min}) corresponds to approximately 69.5% of the ASR above MAS:

Equation 1: Estimated Maximal S_{1min} ($km \cdot h^{-1}$)
$= MAS + 0.695 \times (MSS - MAS)$

For purely linear running performed in unconstrained conditions, Estimated Maximal S_{1min} can reasonably be retained as a reference point for peak locomotor intensity. However, this approach becomes inappropriate for the short-duration, multidirectional, and space-constrained movement patterns that characterise football. In both match and training contexts, spatial constraints inherently limit the attainment and maintenance of a high running speed. As a result, speed-based anchors systematically underestimate intensity in situations where high internal neuromuscular load is generated without prolonged high velocity. This limitation motivates the progression toward a multidirectional, power-based representation of intensity, such as mechanical power, which better integrates both linear and non-linear components of football locomotion (Buchheit & Simpson 2017; Gray, 2025).

Estimated Maximal S_{1min} can be converted to external mechanical power ($W \cdot kg^{-1}$). Speed is first expressed as metabolic power using a standard cost of transport for level running (≈ 4.18 $J \cdot kg^{-1} \cdot m^{-1}$), then converted to external mechanical power assuming $\sim 25\%$ gross efficiency (Arellano 2014; Kaneko 1990). This yields an estimate of maximal 1-min average external mechanical power capacity (Equation 2; Figure 16) that can be compared with GPS-derived mechanical power outputs (Figures 12-13); illustrative examples derived from an elite professional football team are also provided in Table 2.

Equation 2: Estimated Maximal MP_{1min} ($W \cdot kg^{-1}$)
$= 1.045 \times [(MAS/3.6) + 0.695 \times ((MSS - MAS)/3.6)]$

Methodological considerations and limitations of Estimated Maximal MP_{1min}

This approach provides an estimate rather than a direct measurement of maximal mechanical power capacity (Equation 2 and Table 2) and relies on several assumptions. First, the conversion from speed to mechanical power assumes a constant cost of transport (~ 4.18 $J \cdot kg^{-1} \cdot m^{-1}$) and a 25% fixed gross efficiency, which may vary between players (e.g., differences in fiber types, training status, body size, movement patterns; Buchheit 2011). Second, MSS and MAS alone do not capture individual differences in acceleration, deceleration, or change-of-direction ability, which can substantially influence GPS-derived mechanical power. Consequently, Estimated Maximal MP_{1min} should be interpreted as a theoretical reference against which match or training demands can be expressed, rather than as an absolute physiological limit. Importantly, from a practical perspective, the observation that players typically reach $\sim 78\%$ (59 to 97) of this estimated maximal capacity during matches (Table 2) is both coherent and reassuring. Players are required to solve football problems and interact with teammates and opponents, and therefore rarely operate at true all-out capacity (Buchheit, Mendez-Villanueva et al. 2010a; Mendez-Villanueva et al., 2011; Byrkjedal et al., 2024). In this context, consistently observing match intensities just below the estimated maximum supports the internal consistency of the approach. Conversely, systematic values exceeding 100% would be physiologically implausible and would call the underlying assumptions into question.

Intensity Exposure Time (IET) in practice

Choosing the analysis window: short vs long peak periods

The choice of rolling window length (Figure 12) is a critical yet insufficiently justified component of intensity-based GPS metrics. In this paper, emphasis is placed on 1-min rolling windows, largely because they have been used in studies linking peak locomotor demands to injury risk (e.g., Gregson 2020). However, there is no strong physiological or mechanical rationale for privileging 1-min periods over longer windows. Indeed, work examining 3- and 5-min peak periods has shown comparable sensitivity for identifying intense match phases and injury-relevant exposures (e.g., Moreno-Pérez 2024).

What likely matters more than the absolute window duration is the ability to express intensity relative to an appropriate maximal reference, analogous to the anaerobic speed reserve (ASR) concept (Figure 15). When such a reference exists, multiple window lengths can provide meaningful information, provided they are interpreted relative to individual capacity.

Importantly, window duration shapes the nature of the stress captured. Shorter windows (e.g., 5–30 s or 1 min) operate closer to MSS and maximal mechanical power, and therefore likely reflect internal neuromuscular load more directly. This principle is not entirely new and was already implicitly recognised within GPS 2.0 practices. Indeed, sprint exposure was sometimes individualised by examining the distance covered within a single sprint when players reached $\geq 90\%$ of their maximal sprinting speed, rather than the total distance accumulated within a relative speed zone. Conceptually, this approach better reflects neuromuscular loading, as covering ~ 60 m near MSS in one sprint is likely more demanding than accumulating the same distance across multiple shorter efforts. Despite this stronger physiological rationale and occasional practitioner use, such analyses never became mainstream, with practice largely reverting to cumulative, zone-based distance reporting.

In contrast, longer windows (3–5 min) correspond to lower relative intensities, integrating a greater metabolic and cardiovascular component alongside mechanical load. From this perspective, shorter windows may be more relevant for internal neuromuscular load and tissue loading, whereas longer windows may better reflect sustained high-intensity demands.

At present, however, no evidence-based "optimal" window duration exists. Systematic comparisons across window lengths, anchored to individual maximal references and linked to fatigue, adaptation, and injury outcomes, remain a key priority for future research.

Effect of windowing strategy on peak-intensity detection

The example shown in Figure 17 illustrates how the choice of windowing strategy used to segment training and match data can substantially influence the identification of peak intensities and the resulting estimates of time spent in high-intensity mechanical zones. While overlapping rolling 60-s windows provide a continuous assessment of peak demands (Varley 2012), non-overlapping 60-s windows may miss true peaks solely due to differences in temporal alignment. Also, aligning shorter windows (e.g., 45 s) with the actual work periods of conditioning drills (such as 15–30 s tempo runs performed at the end of the session, Figure 17) more accurately captures peak mechanical power and yields higher time-in-zone values. These observations confirm that methodological choices in data segmentation, rather than differences in the underlying physical demands, can drive meaningful variation in reported training load metrics, consistent with previous findings showing that fixed, non-overlapping windows may underestimate peak intensities (Varley 2012).

Setting intensity thresholds: pragmatic heuristics, not physiological anchors

Importantly, neuromuscular intensity thresholds remain exploratory. Unlike heart-rate zones, which are anchored to well-established physiological breakpoints (e.g., ventilatory or lactate thresholds; %HRmax), no equivalent biological anchors currently exist for GPS-derived neuromuscular metrics. As such, thresholds such as 70, 80 or 90% should be interpreted as pragmatic heuristics rather than validated dose–response targets.

In practice, generic thresholds may be used when individual benchmarks are unavailable (e.g., time spent >5 or >6 $W{\cdot}kg^{-1}$). However, advanced applications should preferentially express IET relative to a player's Estimated Maximal MP_{1min} (Table 2), assessed over relevant rolling windows (e.g., 30 s, 1, 3, or 5 minutes; Figure 18 and Table 1).

At this stage, IET should be viewed as an evolving construct. Its principal value lies in redirecting monitoring away from metres accumulated and toward time exposed to meaningful mechanical intensity, while remaining open to future physiological calibration as the evidence base develops.

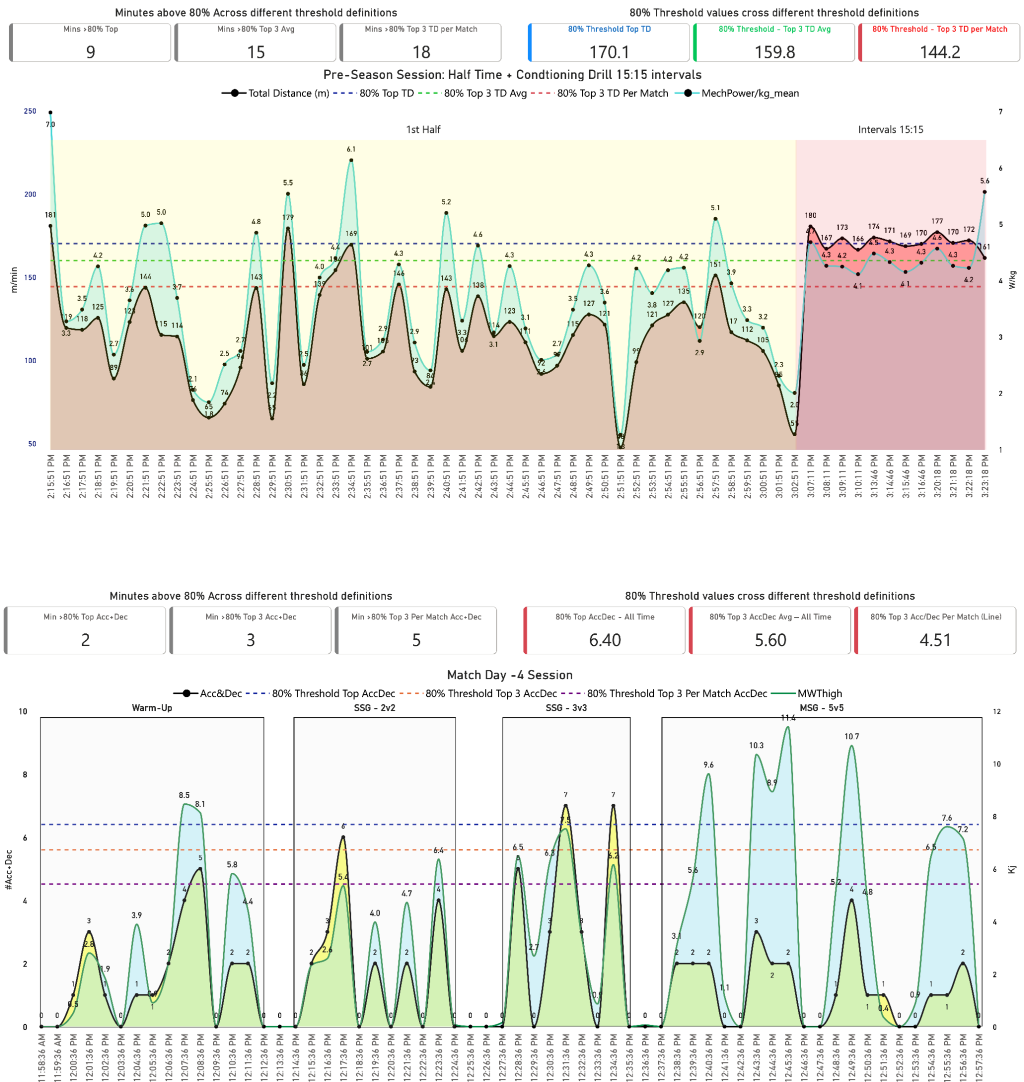


Fig. 14. Example from a single player during two pre-season sessions, illustrating how different methods for defining maximal intensity reference points (MIPs), such as the all-time match peak, the average of the three highest match values, or the mean of selected matches (e.g., best three), produce materially different reference values and, in turn, large differences in calculated Intensity Exposure Time (IET). The session shown in the upper panel includes one half of a friendly match followed by generic, run-based high-intensity interval training, 3 sets of 4 min, 15s on 20%ASR /15s passive, and presents data and intensity thresholds for total distance (TD) and mechanical power (MP). The session shown in the lower panel (various small-sided games, SGG) presents data and intensity thresholds for acceleration–deceleration counts and the thigh-dominant, multidirectional components of mechanical work (MWthigh). Notably, ADI-derived metrics (MP and MWthigh) consistently capture greater exposure than traditional variables (TD and accelerations–decelerations), likely reflecting their sensitivity to non-linear and multidirectional movement patterns that are largely missed by conventional GPS metrics.

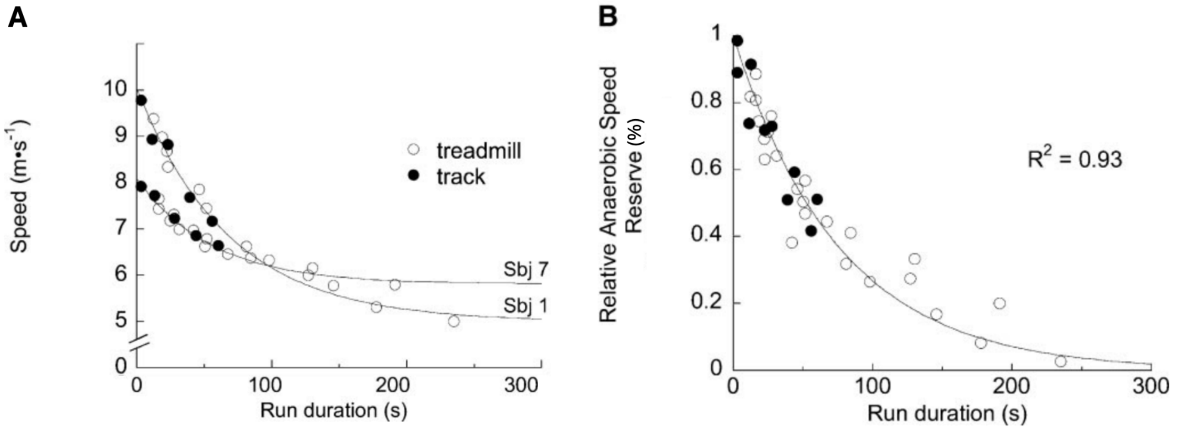


Fig. 15. Adapted from Bundle (2003). Panel A shows all-out treadmill and track running speeds across different run durations for two individuals representing the fastest (Subject 1) and slowest (Subject 7) maximal sprint capacities in the sample. Absolute speeds differ substantially between subjects at any given duration. Panel B presents the same data expressed relative to each subject's anaerobic speed reserve. When normalised to individual capacity, between-subject differences largely disappear, illustrating how expressing intensity relative to maximal locomotor capacity reduces inter-individual variability compared with absolute speed measures.

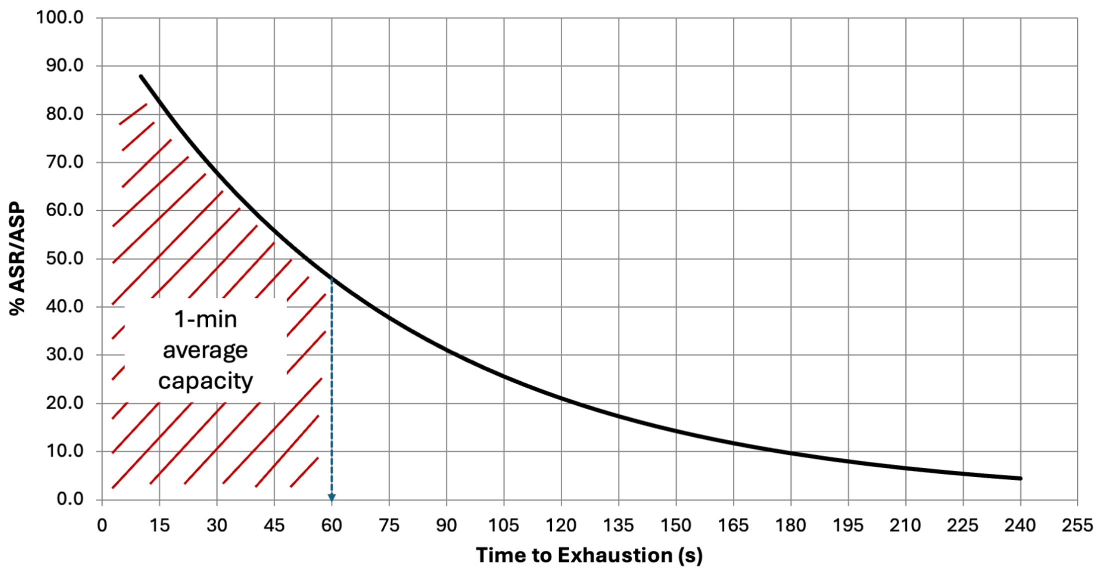


Fig. 16. Conceptual illustration of the Bundle–Weyand speed–duration model (Figure 15) expressed relative to the anaerobic speed reserve (ASR). The black curve represents the instantaneous fraction of ASR that can be sustained during an all-out effort as a function of time to exhaustion, following an exponential decay. The hatched red area highlights the 1-min average capacity, defined as the time-averaged fraction of ASR sustained over a 60-s effort. This average value (≈69.5% of ASR) is used to estimate maximal 1-min mean speed and, after conversion (Equation 2), Estimated Maximal MP_{1min}.

Table 2. Example of professional players locomotor profile (maximal aerobic speed, MAS, estimated from a 1500m time-trial, and maximal sprinting speed, MSS), associated Estimated Maximal MP_{1min} using Equation 2, Peak Match MP_{1min} (best of 3 matches), and Peak Match MP_{1min} expressed as a percentage of Estimated Maximal MP_{1min}.

Player Name	Position	MAS (km/h)	MSS (km/h)	Estimated Maximal MP_{1min} ($W \cdot kg^{-1}$)	Peak Match 1-min ($W \cdot kg^{-1}$)	Peak Match 1-min (% of Estimated Maximal MP_{1min})
Player 1	Central Defender	14.4	33.8	8.1	7.38	91%
Player 2	Central Defender	16.6	32.5	8	7.02	88%
Player 3	Central Defender	15.1	35.7	8.5	5.03	59%
Player 4	Left Back	15.9	37.6	9	6.95	77%
Player 5	Left Back	16.2	36.7	8.8	5.72	65%
Player 6	Right Back	16.6	36.6	8.8	6.41	73%
Player 7	Right Back	15.9	35.6	8.6	5.59	65%
Player 8	Defensive Midfielder	16.3	32.8	8.1	5.67	70%
Player 9	Defensive Midfielder	16.8	34.0	8.4	6.79	81%
Player 10	Central Midfielder	16.3	35.6	8.6	7.13	83%
Player 11	Central Midfielder	16.2	34.0	8.3	6.65	80%
Player 12	Central Midfielder	16.0	35.1	8.5	7.35	86%
Player 13	Central Midfielder	15.0	35.9	8.6	6.83	79%
Player 14	Central Midfielder	16.4	33.5	8.2	5.87	72%
Player 15	Attacking Midfielder	15.7	35.7	8.6	6.91	80%
Player 16	Left Winger	16.8	34.8	8.5	7.57	89%
Player 17	Left Winger	16.0	38.9	9.3	7.65	82%
Player 18	Right Winger	15.9	33.5	8.2	6.1	74%
Player 19	Right Winger	13.8	35.2	8.3	8.05	97%
Player 20	Striker	14.6	35.6	8.5	6.9	81%
Player 21	Striker	14.4	37.3	8.8	5.6	64%
Average		**15.8**	**35.3**	**8.5**	**6.6**	**78%**
SD		**0.9**	**1.6**	**0.3**	**0.8**	**10%**

Integrating ADI-derived metrics and intensity exposure: A rehabilitation case illustration

Figure 18 illustrates the concept of IET for a top international football player, defined as the cumulative time a player spends above a given relative mechanical intensity threshold, calculated from 60-s rolling windows. In this example, thresholds are set at ≥60, 70 and 80% of the individual match-derived MIP for conventional GPS metrics and relative to the palyer's Estimated Maximal MP_{1min} for mechanical power (MP). By moving beyond isolated peak values (Lacome, 2018b), IET provides a time-based description of how long a player is exposed to meaningful intensity across different metrics and contexts (Mandorino, 2024).

When applied to match play and individual return-to-play (RTP) training (Figure 18; Table 3), this framework reveals clear contextual differences. During matches, the player accumulates substantial IET (i.e., 2-6 min) above the 80% match-derived threshold across all metrics, reflecting the rich and continuous neuromuscular stimulus imposed by football-specific activity. Notably, while traditional GPS variables such as high-speed running and acceleration–deceleration frequency tend to appear as relatively binary on–off signals, MW and MP display a more continuous profile and display greater IETs, capturing ongoing locomotor and movement demands even when short bursts do not exceed predefined thresholds.

A similar pattern is observed during RTP training. MW and MP again provide a continuous representation of loading, whereas high-speed running and acceleration metrics remain intermittent. However, despite the apparent ease with which high-speed running and acceleration IET can be accumulated in controlled settings, exposure to high MW_{thigh} (i.e.; 1 min only) and high MP (0 min) remains markedly limited. This likely reflects the difficulty of reproducing the dense, multidirectional, and interactive movement patterns characteristic of match play through individual drill design alone.

Importantly, across both match and RTP training contexts, no time is spent above the 70 and 80% threshold based on Estimated Maximal MP_{1min}. During matches, this is coherent with the tactical and contextual constraints of football, where players must regulate effort rather than express true maximal capacity (Buchheit, Mendez-Villanueva et al. 2010a; Mendez-Villanueva et al., 2011; Byrkjedal et al., 2024). During RTP training, the absence of exposure above this reference likely reflects deliberate load management and/or drills that do not permit maximal mechanical expression. Together, these observations support the use of Estimated Maximal MP_{1min} as a realistic upper reference bound, rather than a routinely attainable target, and indicate that differences in IET primarily reflect contextual constraints rather than true capacity limitations.

Overall, Figure 18 highlights a key limitation of relying on speed- and acceleration-based metrics in isolation. Linear running and isolated accelerations can be readily reproduced in controlled environments, whereas sustained high mechanical work and power, and thus meaningful neuromuscular IET, emerge from complex football-specific actions, including curvilinear running, braking–reacceleration sequences, torso rotations, and multidirectional interactions with teammates and opponents. As such, this example demonstrates both how IET operates in practice and why mechanical work/power and

ADI-derived metrics are particularly valuable for distinguishing generic locomotor loading from genuinely football-specific internal neuromuscular load, especially during return-to-play progression.

Fig. 17. Illustration of how different methods for segmenting a training session influence the identification of peak intensities and the resulting time spent in high-intensity zones, using the simple m/min variable. The upper-left panel shows the raw GPS time series for a representative session (speed and derived metrics). The remaining panels present three alternative splitting strategies applied to the same data: (i) non-overlapping 60-s rolling windows over the entire GPS recording, (ii) non-overlapping 60-s windows starting specifically from the beginning of the session, which differ only by temporal alignment, and (iii) 45-s non-overlapping windows specifically aligned with the work periods of the conditioning block at the end of the session, designed to mimic 15–30 s tempo runs.

Table 3. Summary of Intensity Exposure Time (IET) above the player's 60, 70 and 80% intensity thresholds for key GPS-derived variables, derived from the same data illustrated in Figure 18. Variables include high-speed running (HSR), acceleration–deceleration frequency (Acc+Dec), and mechanical work decomposed into stride-dominated (MW_{stride}) and thigh, multidirectional (MW_{thigh}) components, as well as mechanical power. Note that for mechanical power, the thresholds are also based on the player's Estimated Maximal MP_{1min}.

Reference Threshold	Variable	Threshold values >60 / 70 / 80%	Match IET >60 / 70 / 80%	RTP IET >60/ 70 / 80%
Match MIP_{1min}	TD	109.3 / 127.5 / 145.5 min·min^{-1}	18 / 12 / 5 min	11 / 10 / 8 min
	HSR	25.2 / 29.4 / 33.7 min·min^{-1}	3 / 3 / 2 min	5 / 4 / 3 min
	MW_{stride}	7.5 / 8.8 / 10.1 Kj·min^{-1}	21 / 7 / 4 min	12 / 8 / 4 min
	Acc+Dec	1.4 / 1.6 / 1.9 #·min^{-1}	7 / 7 / 7 min	5 / 5 / 5 min
	MW_{thigh}	7.0 / 8.2 / 9.4 Kj·min^{-1}	12 / 8 / 6 min	4 / 3 / 1 min
	Mechanical Power	3.6 / 4.2 / 4.9 W·kg^{-1}	29 / 10 / 2 min	6 / 1 / 0 min
Estimated Maximal MP_{1min}	Mechanical Power	5.0 / 5.8 / 6.7 W·kg^{-1}	2 / 0 / 0 min	0 / 0 / 0 min

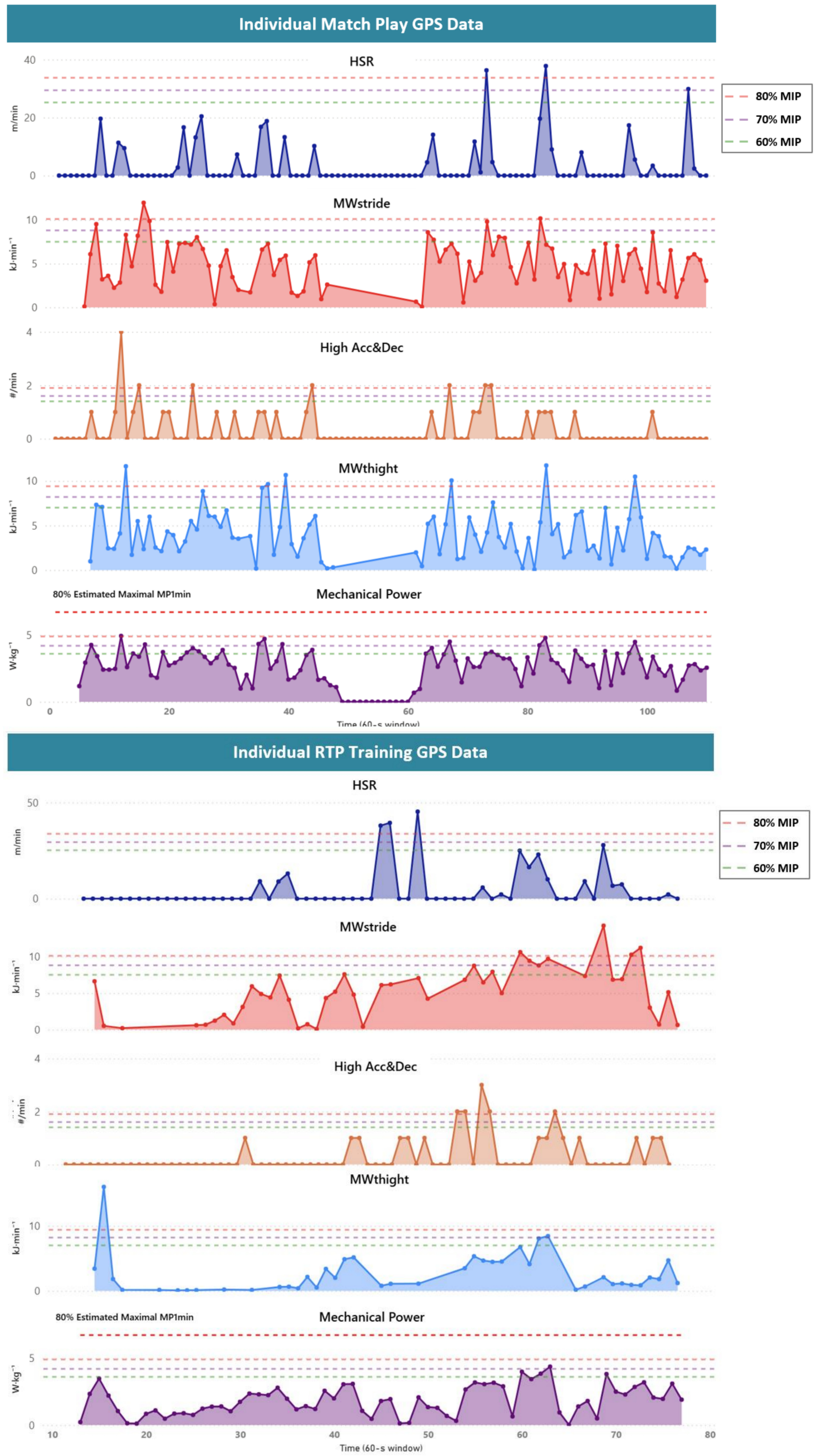


Fig. 18. Example of locomotor intensity profiles derived from 60-s rolling windows across two contexts for a top international football player: match play (Upper) and individual return-to-play (RTP) training (Lower), using common and advanced GPS metrics: high-speed running (HSR; m$\cdot$min^{-1}), acceleration frequency (#$\cdot$min^{-1}), stride-dominated constant speed component of mechanical work (MW_{stride}), thigh, multidirectional accelerations, decelerations and changes of direction component of mechanical work (MW_{thigh}), and mechanical power (MP; W$\cdot$kg^{-1}). For traditional metrics (i.e., HSR, Acc), intensities are expressed relative to the player's match-derived Most Intense Period (MIP), with time spent $\geq$80% of match MIP highlighted as a benchmark. For MP, an additional threshold includes 80% of his Estimated Maximal MP_{1min} using Equation 2.

Weekly Intensity Exposure Time (WIET): Borrowing proven logic from heart-rate dose–response models

If GPS 3.0 aims to move beyond distance accumulation toward meaningful representations of intensity, the logical next step is to shift weekly targets from how much players run to how long they are exposed to high mechanical intensity. This mirrors the evolution already seen in internal load monitoring, where volume-based metrics were progressively complemented by time spent in high-intensity (heart rate) zones (Buchheit & Akubat 2025).

In cardiovascular monitoring, this logic is well established. Rather than relying on average heart rate, practitioners routinely track time spent above critical thresholds (e.g., lactate thresholds, ventilatory break points, ≥85–90% HRmax), with practical guidelines suggesting ∼30 minutes per week above these key intensities to maintain or improve generic aerobic fitness (Buchheit & Akubat 2025). Importantly, this weekly exposure is accumulated across matches and training, which highlights the need for compensatory work in substitutes when match exposure is insufficient (Buchheit, Douchet et al 2024).

The same conceptual framework can apply to neuromuscular load. While the evidence base linking traditional GPS-derived metrics to adaptation or injury remains very limited (Little & Buchheit 2025), it is arguably more coherent to track time exposed to high mechanical intensity than to chase absolute distances accumulated in arbitrary speed zones (Kalkhoven 2021). Distance is an outcome; intensity exposure is the stimulus. But the same principle still applies: the goal is not to 'chase IET minutes'. The goal is to design football (or football-relevant) tasks that expose players to the required mechanical intensity. If training is well designed, IET is observed, not artificially manufactured.

At present, weekly IET targets derived from GPS must be viewed as exploratory rather than prescriptive. Robust dose–response relationships linking IET (whether based on $\text{MW}\cdot\text{min}^{-1}$ or MP) to neuromuscular adaptation, fatigue, or injury risk have not yet been established, and substantially more data are required before optimal doses can be defined.

Data from Tables 4 and 5, drawn from two professional teams (one competing in the UEFA Champions League and one in the Romanian second division), should be interpreted cautiously because they come from different squads and contexts, so any between-team comparison is only illustrative ("with a pinch of salt"). That said, they usefully show (i) how training exposure compares with match exposure across a microcycle, and (ii) how the same "time-above-threshold" logic can be operationalised with two different intensity anchors: match-derived MIP thresholds (Table 4) versus a capacity-based threshold (Estimated Maximal $\text{MP}_{1\text{min}}$; Table 5).

Data from Tables 4 and 5, show that high-intensity IET primarily accumulates on acquisition days (MD–4 and MD–3; Buchheit, Sandua et al., 2021). Using match-MIP–anchored thresholds (Table 4), weekly training exposure can be comparable to (and sometimes exceed) match exposure at moderate relative intensities (e.g., >60%: 43.1 ± 9.6 min in the training week vs 31.3 ± 3.6 min in the match; >70%: 21.1 ± 7.1 vs 16.9 ± 2.6), while the very highest band may remain hard to "replicate" in training (e.g., >80%: 6.6 ± 4.9 in the training week vs 7.4 ± 1.3 in the match).

Even during these sessions however, overall weekly exposure remains very low relative to individual maximal capacity, typically amounting to only ∼5–15 minutes above 60–70% of Estimated Maximal $\text{MP}_{1\text{min}}$ across the entire microcycle (Table 5). Match exposure itself is similarly limited, with players accumulating ∼5 minutes above 60% of Estimated Maximal $\text{MP}_{1\text{min}}$ during competition (Table 5). In practice, Table 5 illustrates how a capacity-based anchor "tightens" the interpretation: when thresholds are expressed relative to Estimated Maximal $\text{MP}_{1\text{min}}$, both training and match exposures drop markedly (training week total: 14.8 ± 6.4, 4.1 ± 3.1, 0.5 ± 0.6 min above 60/70/80%; match: 4.8 ± 1.5, 1.2 ± 1.5, 0.2 ± 0.4), reinforcing that players rarely spend meaningful time near their true 1-min mechanical ceiling in either context.

This consistently low IET reinforces a central point of the manuscript: players rarely express near-maximal mechanical intensity over 1-min windows, whether in training or competition. While weekly IET often exceeds match exposure when summed across the microcycle (Tables 4 and 5), individual training sessions typically accumulate only ∼50% of the time spent above high-intensity thresholds observed during matches, rather than reproducing equivalent peak exposure within a single session. Taken together, Tables 4–5 also make the applied trade-off explicit: match-MIP anchors are intuitive for match-preparation benchmarking, but they remain context-driven and can make exposure look "higher" than it truly is in biological terms; capacity-based anchors better indicate how close the player got to their maximal mechanical potential, so they can move us closer to internal neuromuscular load inference, yet they still yield very low minutes at high thresholds. Crucially, even the best physics-based external metric will always remain a proxy. In other words, GPS can shift from a poor to a better proxy of internal load, but it will never "be" internal load until true internal measures are available and scalable.

From a preparation perspective, this raises two important implications. First, current training practices may underexpose players to the intensity structure of competition, even when traditional distance-based metrics suggest relatively high loads (e.g., MD–3 sessions reaching ∼60–80% of match distance in speed zones; Buchheit, Sandua et al., 2021). Second, the limited expression of high-intensity IET over 1-min windows suggests that shorter windows (e.g., 10–15 s), closer to the duration of football action sequences, may better capture and reflect internal neuromuscular load and tissue loading than longer rolling averages. Whether such shorter windows provide greater sensitivity to fatigue, adaptation, or injury risk remains unknown and should also be a priority for future research.

In summary, weekly IET offers a more coherent organising framework than distance or ratio targets, but its interpretation remains provisional. Clarifying optimal exposure durations, meaningful intensity thresholds, and appropriate window lengths, as well as their links to neuromuscular outcomes, will require systematic investigation before IET can move from a descriptive construct to an evidence-informed auditing tool.

Weekly Intensity Exposure Time (WIET): learning from GPS 2.0 mistakes

Importantly, WIET does not prescribe how intensity should be achieved. Football-specific drills, conditioned games, or targeted exercises can all contribute, provided they genuinely expose players to the required mechanical intensity. However, the same pitfalls observed in GPS 2.0 remain possible: just as distance-into-zone targets led to non-specific running designed merely to "tick the box," WIET could be artificially accumulated through generic or poorly contextualised tasks that satisfy the metric without delivering meaningful football-specific stress.

As with heart-rate–based approaches, the value of WIET lies in shifting attention from total accumulation to exposure quality, but only if task design remains football-led. When intensity metrics become the objective rather than the audit tool, the framework risks reproducing the very errors GPS 3.0 seeks to correct.

Weekly IET targets should therefore be viewed as guiding principles rather than fixed prescriptions. While evidence-informed thresholds will require further work, focusing on exposure to intensity, rather than metres or ratios, represents a more biologically coherent direction for a GPS-based 3.0 load monitoring.

Table 4. Example of time spent >60, >70 and 80% of Players' peak Match MP_{1min} during a typical weekly microcycle in a Ligue 1/ UEFA Champions League team (Average of 7 players). Only full matches data included.

	>60% peak match MP_{1min} (min)	>70% peak match MP_{1min} (min)	>80% peak match MP_{1min} (min)
MD+1	Day Off	Day Off	Day Off
MD+2	9.1 ± 2.4	4.7 ± 1.2	1.1 ± 1.6
MD+3/-4	8.9 ± 2.2	5.0 ± 1.0	3.1 ± 1.0
MD-3	17.1 ± 6.7	7.3 ± 4.2	1.6 ± 1.5
MD-2	4.7 ± 0.8	3.0 ± 1.7	0.7 ± 1.3
MD-1	3.3 ± 1.3	1.1 ± 0.7	0.0 ± 0.0
Training week total	43.1 ± 9.6	21.1 ± 7.1	6.6 ± 4.9
Match	31.3 ± 3.6	16.9 ± 2.6	7.4 ± 1.3

Table 5. Example of time spent >60, 70 and 80% of Players' Estimated Maximal MP_{1min} during a typical weekly microcycle in a Romanian second league team (Average of 12 players). Only full matches data included.

	>60% Estimated Maximal MP_{1min} (min)	>70% Estimated Maximal MP_{1min} (min)	>80% Estimated Maximal MP_{1min} (min)
MD+1	Day Off	Day Off	Day Off
MD+2	2.2 ± 2.8	0.5 ± 1.4	0.0 ± 0.0
MD+3/-4	2.7 ± 1.9	0.8 ± 0.9	0.3 ± 0.6
MD-3	7.8 ± 4.2	2.5 ± 1.8	0.3 ± 0.5
MD-2	0.4 ± 0.9	0.1 ± 0.5	0.0 ± 0.0
MD-1	1.3 ± 1.5	0.2 ± 0.6	0.0 ± 0.0
Training week total	14.8 ± 6.4	4.1 ± 3.1	0.5 ± 0.6
Match	4.8 ± 1.5	1.2 ± 1.5	0.2 ± 0.4

Conclusion: GPS stays, GPS 2.0 goes. Enter GPS 3.0

GPS is not the problem. How it has been used is.

Over the past two decades, GPS has become central to load monitoring in elite football. However, GPS 2.0, largely built around distance-based zones, averages, and ratios, has drifted beyond its rightful place in the load–response framework, with external metrics routinely interpreted as direct proxies of internal neuromuscular load, readiness, or injury risk. This occurred while overlooking the low strength of these measures for capturing neuromuscular load, particularly when quantity was prioritised over intensity. The result has been volume norms chasing, ratio policing, and behaviours that favour dashboard compliance over proper preparation (Little & Buchheit, 2025).

GPS 3.0 represents a necessary recalibration. It repositions GPS firmly within the upper-right quadrant, as a tool to only characterise external mechanical exposure rather than internal biological load. By shifting the focus from metres and ratios to how intensity is structured and expressed, through Most Intense Periods (MIPs, Figure 13), (weekly) Intensity Exposure Time (IET, Table 3 & 4), mechanical work and power, and movement signatures (Figure 9), GPS can inform training instead of dictating it. Importantly, many concepts discussed here remain promising but not yet fully validated; their immediate value lies in explicitly acknowledging measurement limitations, prioritising intensity before quantity, and clarifying where further research is most needed (e.g., window duration, physiological anchoring, links to adaptation, fatigue and injury).

From a practitioner's perspective, an applicable GPS 3.0 "today" is pragmatic rather than perfect. It involves (i) anchoring intensity to individual reference capacities (e.g., relative speed thresholds, individual estimated maximal 1-min values), (ii) complementing peaks with IET to describe exposure time rather than meters accumulation, and (iii) interpreting mechanical work and power as indicators of movement richness, not precise dose metrics.

Why IET isn't solvable with GPS 2.0 variables alone

Intensity Exposure Time is only meaningful if the intensity metric reflects how football actually generates neuromuscular load: through combined linear + multidirectional mechanics within the same window. Traditional GPS 2.0 variables (speed-zone distance, HSR, isolated acceleration counts) are too partial to represent that integrated mechanical demand.

A simple numerical sanity-check shows why. Sustaining ~7–8 $W \cdot kg^{-1}$ over 60 s represents a near-maximal mechanical demand (Figure 12, Table 2). If we tried to express that same 1-min intensity using linear running alone, it would imply continuous running at ~28 $km \cdot h^{-1}$ for 60 s (~480 $m \cdot min^{-1}$); a scenario essentially never observed in football matches. If we tried to express it using accelerations/decelerations alone, it would require an implausibly dense sequence (e.g., on the order of ~12–15 high-intensity accel–decel cycles per minute while still playing football). Yet match-derived 1-min MIPs for total distance are typically ~180–210 $m \cdot min^{-1}$, which corresponds to only ~4–5 $W \cdot kg^{-1}$ if interpreted as linear running (Tables 1 and 3). The "missing" intensity is exactly the multidirectional work (curves, braking–reacceleration, and direction change) occurring within the same minute.

This is also why, in rehabilitation practice, the logic should remain football-action first: drills are designed to recreate match-like movement sequences (curves, decel–reaccel, turns, orientation changes, interactions), and GPS is then used to audit whether the intended integrated peak demand occurred within the same window, rather than to "chase" a single metric (e.g., HSR distance or accel counts) in isolation. Video examples of these football-specific rehab drills (links: large and close views) can be referenced here to illustrate how high mechanical intensity can be generated with modest HSR totals, and why integrated MW/MP is required to capture it.

Therefore: if you do not have direction-sensitive MW/MP (or an equivalent mechanic-integrated construct), do not pretend IET is "implemented." You can still report time-above-threshold for GPS 2.0 metrics, but it should be framed as variable-specific exposure descriptors, not a unified neuromuscular intensity exposure model.

GPS 3.0 "tomorrow"

Looking ahead, an applied GPS 3.0 will require closer integration between improved external metrics and complementary internal, metabolic, or tissue-level measures, alongside clearer physiological calibration of intensity thresholds and stronger evidence linking exposure patterns to adaptation, fatigue and injury outcomes. While capacity-based models such as those derived from the work of Bundle provide a coherent framework to link mechanical output, neuromuscular fatigue, and metabolic cost during continuous, all-out exercise, their direct translation to football remains limited. Football is characterised by highly intermittent, multidirectional efforts, where the relationship between external mechanical work, metabolic disturbance, and muscle fatigue is far less deterministic.

Critically, identical IET values may reflect very different physiological consequences depending on whether high-intensity periods are continuous or interspersed with recovery. Consecutive exposures at a given intensity are likely far more metabolically and neuromuscularly demanding than the same external work accumulated with intermittent recovery, despite equivalent IET. This highlights that even within a GPS 3.0 framework, substantial uncertainty remains when inferring true muscle load and fatigue from external data alone. Consequently, the use of heart rate and other internal measures as complementary indicators remains essential to contextualise mechanical exposure and better capture the metabolic and systemic consequences of training, as recently re-emphasised by Buchheit and Akubat (2025).

GPS 3.0 does not promise certainty or optimal doses. What it restores is coherence. Metrics should align with mechanics, preparation with football actions, and monitoring with the realities of performance and injury risk. Plan football first; running follows. Any framework, old (distance), current (ratios), or new (IET), fails the moment it dictates training design instead of auditing whether football preparation has actually occurred.

Key Points

- **GPS 2.0 drift:** Distance-in-zones, averages and ratios are useful descriptors, but they are routinely over-interpreted as proxies of internal neuromuscular load, a conceptual leap GPS can't justify.
- **Why it matters:** Identical external locomotor totals can hide very different tissue stress. Football load is multidirectional, highly context-dependent, and partly non-locomotor, so linear GPS summaries can miss a large share of the work actually performed (up to ∼70% in our example; see Figure 9).
- **GPS 3.0 shift:** The priority upgrade is not new hardware but direction-sensitive mechanics, capturing complete acceleration and separating linear vs non-linear demands (e.g., ADI-type analytics).
- **Mechanics first:** Mechanical Work (MW) and Mechanical Power (MP) offer a more coherent external neuromuscular proxy than speed/distance alone, and $\mathrm{MW_{thigh}}$ vs $\mathrm{MW_{stride}}$ separation improves specificity when needed.
- **Peaks > Totals:** Quantify intensity structure via Most Intense Periods (MIPs) (e.g., 30 s–5 min) derived from MW/MP rather than chasing single-metric peaks (HSR, acc counts) in isolation.
- **Intensity reference:** Express intensities against a clear reference: match MIPs can help describe/prepare match demands but are context-driven and unstable, so if one anchor must be chosen, prefer a capacity-based reference (Estimated Maximal $\mathrm{MP_{1min}}$, Eq. 2) so both match and training can be reported as % of peak capacity for more robust load quantification.
- **Exposure is promising, not finished:** IET/WIET reframes monitoring as time exposed to high mechanical intensity, but thresholds and windowing remain method-dependent; treated as exploratory until calibrated.
- **Utopia:** Internal neuromuscular load. Even with more accurate physics-based metrics, GPS can only better quantify external mechanical load; it will still not directly measure internal neuromuscular load.
- **Avoid the GPS 2.0 trap again:** No metric (distance, ratios, MIPs, IET) should become a session-design KPI: plan football first; metrics audit whether the intended exposure occurred.
- **Generic running should be minimised and justified:** When unavoidable, it should be modified to increase mechanical relevance (e.g., curves, direction changes, ball involvement).
- **Method development & standardisation:** Determine the most valid and practical way to operationalise MW/MP-based intensity structure and exposure in football, i.e., optimal window lengths (potentially <1 min), linear vs non-linear decomposition, and robust reference choices (match MIPs vs capacity-based anchors), so results are comparable across teams, contexts and technologies.
- **Dose–response testing:** As done for internal-load models, establish whether GPS 3.0 metrics (direction-sensitive MW/MP, MP-based MIPs, IET/WIET) show stronger, more consistent relationships with meaningful outcomes (fatigue/recovery markers, performance changes, availability/injury events) than GPS 2.0 distance/zone/ratio metrics—i.e., whether improved mechanics actually produces improved biological interpretability.

Interim solutions for GPS 2.0 (implement now, even if GPS 3.0 analytics are unavailable)

- **Individualise speed thresholds:** Use relative thresholds anchored to locomotor profile (MAS, MSS, ASR, V_{IFT}) rather than absolute zones.
- **Separate origins of running:** Report football-derived vs generic running separately in dashboards, ratios, and reports.
- **Use peak periods sparingly:** If using MIPs with traditional metrics, treat them as descriptive only, and avoid single-metric optimisation (e.g., chasing HSR MIPs in isolation).

GPS 3.0 essentials (ASAP)

- **Direction-sensitive mechanics:** Use direction-aware analytics to quantify complete acceleration and separate linear vs non-linear demands (e.g., ADI-derived movement signatures; Figures 7–9).
- **Mechanically grounded load metrics:** Prioritise Mechanical Work (MW) and Mechanical Power (MP) over distance-in-speed zones for neuromuscular interpretation.
- **Source-specific interpretation:** When specificity is required, separate MW_{thigh} (accelerations, decelerations, changes of direction) from MW_{stride} (stride-dominant constant speed high-speed running) (Figures 13 and 18).
- **Peak structure first:** Characterise peak external mechanical exposure using rolling-window peak periods (e.g., 30 s, 1, 3, 5 min; Figures 12–13).
- **Peak periods reference choice depends on purpose:** Peak match MIPs are useful to prepare for match demands, whereas capacity-based anchors (e.g., Estimated Maximal MP_1min, Eq. 2) are better to quantify load; match MIPs are context-driven, less stable, and often dissociated from true maximal capacity.
- **Single reference option:** Anchor intensity to Estimated Maximal MP_1min; match and training can both be expressed as % of peak capacity, avoiding the instability of match-MIP references.
- **Context tagging:** Tag outputs by drill type and constraints (e.g., generic vs football-specific, opposition, pitch size, rules, player role/status) to prevent "equivalent totals, different stress" misinterpretation.

What GPS 3.0 should explicitly avoid

- Stand-alone weekly distance/HSR totals interpreted as internal neuromuscular load.
- Arbitrary HSR/sprint quotas disconnected from context and movement signature.
- Training-to-match ratios used in isolation without origin, distribution, and drill context.
- Using any locomotor metric (distance, ratio, IET) as a session-design KPI rather than an audit tool.

Hudl ADI's Mechanical Work & Power: A Physics-Based Approach to Load
To move beyond the limitations of distance-based metrics, ADI's Mechanical Work and Power metrics quantify the total external mechanical load by applying fundamental physics to the athlete's movement. Rather than treating locomotion as simple linear displacement, this approach calculates the energy required to manipulate the athlete's center of mass in a multidirectional environment.

The Intensity Metric: Mechanical Power (MP). Mechanical Power represents the instantaneous mechanical intensity of movement, normalized to the athlete's body mass ($W \cdot kg^{-1}$). The algorithm derives this by summing two distinct mechanical demands at every sampling point:

- **Power to Maintain Speed:** This component accounts for the mechanical cost of keeping the body in motion at the current velocity. It explicitly recognizes that even during constant-speed running, an athlete must generate force to overcome gravity and vertical oscillation.
- **Power to Accelerate (Complete Acceleration):** This component captures the additional power required to change the velocity vector. Crucially, and in alignment with GPS 3.0 principles, this utilizes the Acceleration Vector Magnitude (AVM). By incorporating the rate of change of the full velocity vector, the metric accounts for both linear changes in speed and changes in direction/turning. This ensures that the high mechanical demands of curvilinear running and cutting are weighted appropriately alongside linear sprinting.

The Volume Metric: Mechanical Work (MW). By integrating the Total Power value (Watts) over the duration of the specific drill or session, the continuous intensity signal is converted into a cumulative volume metric: Mechanical Work (measured in kJ).

This process provides a single, integrated value representing the total mechanical volume of the session—capturing the hidden load of multidirectional play that traditional speed-based zones routinely miss.

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